The British Energy Market Reform: Carbon Prices, Retail Tariffs, and Cost Pass-through

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Declaration

This thesis is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and specified in the text. It is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my thesis has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee

This thesis contains fewer than 60,000 words including appendices, bibliography, footnotes, tables and equations. Chapter 1 is my independent work. Chapter 2 has been written in collaboration with Dr. Chi Kong Chyong and Prof. David Newbery and my contribution accounts for 35% of the work. Chapter 3 has been written in collaboration with Prof. David Newbery and my contribution accounts for 50% of the work. Chapter 4 has been written in collaboration with Dr Griogio Castagneto Gissey, and my contribution accounts for 70% of the work. Chapter 5 has been written in collaboration with Dr. Melvyn Weeks and my contribution accounts for 50% of the work. Chapter 6 is my independent work.

At the time of submitting, Chapter 2 has been published in the Energy Journal, Chapter 3 is under review at the Journal of Environmental Economics and Management, Chapter 4 received a review-and-resubmission request from the Energy Economics, Chapter 5 is in preparation to submit.

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Abstract

The United Kingdom's (UK's) *Climate Change Act 2008* sets a "net zero" target on greenhouse gas emissions by 2050. The Act has triggered the Electricity Market Reform (EMR) started in 2013, which aims at decarbonising electricity supply, ensuring the security of supply, and minimising the cost of energy to consumers. This thesis focus on policies and instruments that support the EMR. Chapter 1 provides a review of the UK's Climate Change Act, with a focus on the energy sector. Chapters 2 and 3 focus on the British decarbonisation policy levied on the electricity sector. Chapter 4 studies competition in the wholesale electricity market, to investigate the existence of market power. Chapter 5 examines the impact of dynamic retail tariffs and demand response, which are possible instruments to secure electricity supply. Chapter 6 concludes.

Decarbonisation requires increasing the capacity of renewable energy to phase out carbon insensitive fossil plants, and the British Carbon Price Support (CPS, a carbon tax) gives adequate, credible and sufficiently durable carbon price signals for low-carbon investments. Chapter 2 studies the impact of the CPS on the CO_2 emission reduction of wind in the Great Britain's (GB's) electricity market. We show how to measure the Marginal Displacement Factor (MDF, tonnes CO2/MWh) of wind. The short-run (SR) MDF is estimated econometrically while the long-run (LR) MDF is calculated from a unit commitment model of the GB system in 2015. We examine counter-factual fuel and carbon price scenarios. The CPS lowered the SR-MDF by 7% in 2015 but raised the LR-MDF (for a 25% increase in wind capacity) by 18%. We discuss reasons for the modest differences in the SR- and LR-MDFs.

Being a unilateral carbon tax, the CPS can distort electricity trade with external markets. Chapter 3 shows how to estimate the deadweight cost of the distortion and possible external global benefits from reduced emissions, and investigate econometrically the impact of the CPS on GB's cross-border electricity trade with France and The Netherlands. Over 2015-2018 the CPS raised GB day-ahead electricity price by about €11/MWh, after allowing for replacement by cheaper imports. It raised French wholesale prices by 3.5% and Dutch wholesale prices by 2.8%. The CPS increased GB imports by 12 TWh/yr, thereby reducing carbon tax revenue by 100 m/yr. Congestion income increased by €150 m/yr, half transferred to foreign interconnector owners. The unilateral CPS created €80 m/yr deadweight loss,

about 32% of the initial social value created by the interconnector, or 4% of the global emissions benefit of the CPS at €2 bn/yr. About 0.9% of the CO_2 emission reduction is undone by France and The Netherlands, the monetary loss of which is about €18 m/yr.

Cost pass-through rates give a useful perspective of market competition, which determines whether consumers are overwhelmed by the market power. Chapter 4 studies how generation costs are passed through to electricity wholesale prices in GB between 2015 and 2018. Our empirical results fail to reject 100% pass-through rates for gas prices, carbon prices, and exchange rates, indicating a competitive GB wholesale electricity market. We observe higher pass-through rates in peak compared to off-peak periods, because generators bidding at a lower rate during off-peak periods to supply at minimum load to avoid the cost of shutting down and starting up. We extend the argument by assessing generators' bidding behaviour. The study also considers how two key events occurred during the examined period – the drastic decline in the GBP/EUR exchange rate since the Brexit referendum, and major reformation of the EU Emissions Trading System – have affected the electricity bill to a typical domestic household, showing that they have increased the average annual bills by €49(£41)/year/household, or a 7% rise.

Finally, one possible solution to the security of electricity supply is demand response, which is usually achieved through dynamic tariffs by offering consumers financial incentives to shift or reduce peak load to off-peak periods. In Chapter 5, we construct an agent-based model in which the retailer sets dynamic tariffs to maximize profit, and consumers respond to the prices. The model suggests that in the baseline scenario, the dynamic tariff would generate for the retailer an additional €7.35 of annual profit from the average household. For a firm equal in size to British Gas in 2017, this is equivalent to €40 million of total benefit. With market regulations, the dynamic tariff will benefit consumers and retailers alike, resulting in a win–win condition. We also find that the interaction between demand-side management stimuli and market regulation can further reduce consumer-level electricity demand, increase retail profit, and lower consumers' electricity bills.

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Nomenclature

Acronyms / Abbreviations

ARA Rotterdam Coal Futures

ARCH Autoregressive Conditional Heteroskedasticity

BEIS The Department for Business, Energy and Industrial Strategy

BIC Bayesian Information Criterion

BritNed The interconnector linking GB and The Netherlands

BTA Border Tax Adjustment

CCC Committee on Climate Change

CCC Constant Conditional Correlation

CCGT Combined Cycle Gas Turbine

CCL Climate Change Levy

CCS Carbon Capture and Storage

CERT Carbon Emissions Reduction Target

CESP Community Energy Saving Programme

CET Carbon Emission Tax

CF Capacity Factor

CfD Contracts for Difference

CHP Combined Heat and Gas

CO_2 Carbon Dioxide

CPF Carbon Price Floor

CPP Critical Peak Pricing

CPS Carbon Price Support

CV Coefficient of Variation

DCC Dynamic Conditional Correlation

DECC Department of Energy and Climate Change

DF Displacement Factor

DR Demand Response

DSM Demand-side Management

EC Error Correction

ECO Energy Company Obligation

EMR Electricity Market Reform

ETS Emissions Trading System

EU European Union

EUA European Emission Allowance

EUR Euro

EV Electric Vehicle

FiT Feed-in Tariff

GARCH Generalised Autoregressive Conditional Heteroskedasticity

GB Great Britain

GBP Great Britain Pound

GCV Gross Calorific Value

GHG Greenhouse Gas

GW Gigawatt

HHV Higher Heat Value

IED Industrial Emissions Directive

$IESMT$ Irish Electricity Smart Metering Trial

IFA The interconnector linking GB and France

$LASSO$ Least Absolute Shrinkage and Selection Operator

LCP Large Combustion Plant

LEC Levy Exemption Certificate

LHV Lower Heat Value

LR Long-run

$M - GARCH$ Multivariate Generalised Autoregressive Conditional Heteroskedasticity

$MAPE$ Mean Absolute Percentage Error

MDF Marginal Displacement Factor

MEF Marginal Emission Factor

MSR Market Stability Reserve

MW Megawatt

MWh Megawatt Hour

MWh_e Megawatt Hour of Electricity

MWh_{th} Megawatt Hour of Thermal Heat

NBP National Balancing Point

NCV Net Calorific Value

$OCGT$ Open Cycle Gas Turbine

$Ofgem$ Office of Gas and Electricity Markets

OLS Ordinary Least Squares

$O\&M$	Operation and Maintenance
PS	Pumped Storage
PTR	Pass-through Rate
PV	(Solar) Photovoltaic
RD	Residual Demand
RHI	Renewable Heat Incentive
ROC	Renewable Obligation Certificate
RTE	The French Transmission System Operator
RTP	Real-time Pricing
SCC	Social Cost of Carbon
$SEMO$	Single Electricity Market Operator
SMP	Spot Market Price
SR	Short-run
SUR	Seemingly Unrelated Regression
tCO_2	Tonne of CO_2
TOU	Time-of-use
TWh	Terawatt Hour
UK	United Kingdom
US	United States
USD	United States Dollar
$VECM$	Vector Error Correction Model

Chapter 1

A Decade of the UK Climate Change Act: With a focus on the power sector

1.1 Introduction

Aiming at creating an unprecedented legal architecture for the British climate action, the Parliament of the United Kingdom (UK) passed the Climate Change Act (hereafter Act) at the end of 2008 (CISL [39]).

Being one of the earliest binding and long-term framework laws on climate governance globally, the Act enjoys the following five features (Fankhauser et al. [58]). First, it sets a statutory long-term emission target, mandating that the total greenhouse gas (GHG) emissions (within the UK) in 2050 must be at least 80% lower than the 1990 level. This target can be gradually achieved by incorporating the second feature, which sets five-year carbon budgets on a rolling basis. Each budget would provide a five-year, statutory cap on the total GHG emission over that period. The third feature is the provision of continual adaptation planning by introducing climate change risks and adaptation responses to public and private sectors for decision-making. Fourth, the Act created an independent advisory body, namely the Committee on Climate Change (CCC), to recommend and monitor mitigation and adaptation, and to enhance the long-term credibility of the Act. Finally, the Act assigns clear responsibilities and reporting obligations on the government to account to the Parliament, third parties (such as the CCC) and the court (if necessary) to ensure climate policy remains on track.

This chapter gives an overview of the achievement of the UK's Climate Change Act during the past decade, in particular in the power sector. It also discusses lessons for other countries. In Section 1.2, we focus on decarbonisation policies levied on the power sector and discuss the associated impacts. Section 1.3 briefly summarises decarbonisation processes in other sectors. Section 1.4 discusses the UK's achievements on emissions reduction and lessons for other countries. Section 1.5 gives the roadmap to meet the newly proposed net-zero target by 2050 and the potential challenges. Finally, Section 1.6 concludes.

1.2 Impacts on the power generation sector

GHG mitigation in the power generation sector was the government's highest priority for tackling climate change in 2008. It has triggered the Electricity Market Reform (EMR) which aims at decarbonising electricity supply, minimising the cost of energy to consumers, and ensuring the security of supply. Some policies introduced in this section, such as Contracts for Difference and Carbon Price Floor, were part of the initial EMR package. Other policies also contributed to the emissions reduction in the UK, including policies subsidising renewable energy and the EU air quality Directives, and we will discuss those policies in detail in this section.

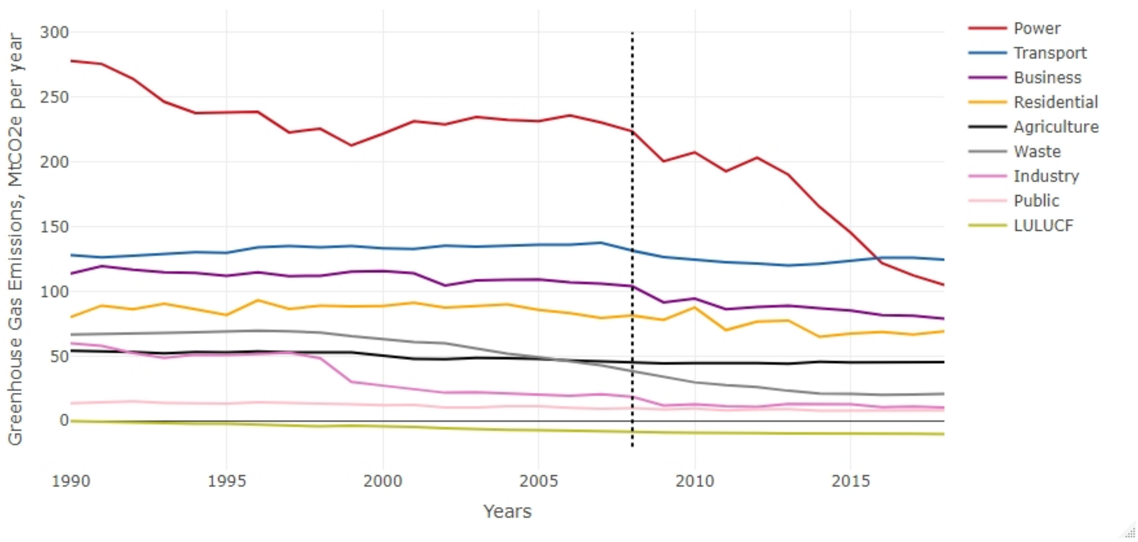
Figure 1.1 presents the UK's GHG emissions by sectors between 1990-2019. Since 2008, the UK's total GHG emissions have been reduced by 33.4% from 643 $MtCO_2e$ to 435 $MtCO_2e$.[1] About 62% of the total GHG emissions reduction since 2008 came from the power sector.

The profound success in decarbonising the power sector mainly came from displacing fossil fuels by renewable energy such as wind and solar photovoltaics (PV). Electricity generated from fossil fuels has been drastically reduced from 76% in 2008 to 46% in 2018,[2] and in 2019 the UK generated more electricity from renewables than fossil fuels for the first time since the Industrial Revolution. The UK's carbon intensity of electricity generation has been drastically reduced from 0.496 tCO_2/MWh in 2008 to (expected) 0.233 tCO_2/MWh in 2020.[3]

Another factor that drives the successful decarbonisation is switching the baseload supply from coal-fired power plants to CCGTs. In 2008, about 29.5% of domestic electricity demand came from coal. This number was reduced to 1.6% in 2019. Besides carbon taxes, the gradual phase-out of coal-fired power plants over the past five years also played a non-trivial role. To some lesser extent, the lower domestic electricity generation also contributed to the GHG emissions reduction. In 2018, the UK's domestic electricity generation fell by 14.5% relative to the 2008 level.

[1] See GOV.UK
[2] See energyscanner.
[3] See GOV.UK.

Fig. 1.1 The UK's Greenhouse Gas Emissions by Sectors, 1990-2019



Source: 2018 UK Greenhouse Gas Emissions, Final figures.

The drastic change was mostly brought about by energy policies such as carbon prices, renewable subsidies, demand-side policies, and air quality directives (regulations). In the rest of this section, we will focus on each of these policies and discuss their impacts on decarbonising the power sector.

1.2.1 Carbon prices

The UK electricity sector has been participating in the EU Emission Trading System (ETS) since its first introduction in 2005. It will remain in the system until 31 December 2020. The EU ETS is a "cap and trade" scheme where a total emission cap is set each year. Large GHG emitters are allowed to trade the emission permits with one another. Hence the ETS price is fluctuating based on the supply and demand of the total emission permits. On top of the ETS, the British electricity generators also pay a fixed carbon tax called the Carbon Price Support (CPS), introduced in 2013 and stabilised at £18/tCO_2 since 1 April 2015.

The merit order effect ranks the available sources of electricity supply based on ascending order of (marginal) prices, formulating the electricity supply curve. The two carbon prices (the ETS and the CPS) have made coal the more expensive fuel (than gas) in Britain's electricity generation. Therefore, a newly built wind farm (who has close-to-zero marginal cost of electricity generation) would displace the more carbon-intensive fuel (i.e. coal instead of gas), substantially reducing GHG emissions (See Chapter 2).

The future of the UK carbon price remains unclear. The latest policy paper published by Her Majesty's Revenue and Customs (HMRC [79]) proposes several possibilities to replace the EU ETS. On the one hand, the government has proposed a Carbon Emission Tax (CET) in its Budget 2018 (HMRC [78]). The CET will cover all stationary installations that are currently participating in the EU ETS, and the proposed rate was £16/tCO_2. Another possibility is to have an Emission Trading System for the UK, which replaces the EU ETS. It is possible to link the UK ETS with the EU ETS if it meets both sides' interests. Either way, the aim is to maintain a high carbon price in the electricity sector so that the UK would meet its ambitious 2050 GHG emission target.

Using LCP's EnVision model of the GB power sector, Ofgem [116] concludes that carbon pricing is the most important policy in achieving GB's decarbonisation targets, contributing more emissions reduction than the combination of renewable subsidies, demand-side policies, and air quality directives. In Chapter 2, we estimate that in 2015 the CPS reduced the total GHG emissions in the GB electricity system by 44.5 MtCO_2, or 5.6% of the total GHG emissions in 1990.

Despite the fact that the CPS has substantially reduced GHG emission in the GB power generation sector, other EU countries refused to introduce a comparable carbon tax to match.[4] As GB is currently trading electricity with several continental countries via interconnectors (i.e. underwater electricity cables), the unilateral CPS would distort trade and result in carbon leakage. In Chapter 3, we estimate that between 2015-2018, the monetary value of trade distortion is €80 million/year, or about 32% of the social value (i.e. market surplus from trading) created by the interconnector. We also estimate that about 0.9% of the CO_2 emissions reduction from the CPS was undone by France and The Netherlands.

At the time of writing, GB is interconnected with France, Belgium, The Netherlands, and the island of Ireland. There are three more interconnectors under construction and two more in early development. The trade distortion and carbon leakage can be much greater as interconnector capacity increases. This could be resolved via equalising the carbon prices between GB and the EU, probably by convincing the EU to implement a carbon tax that is similar to the British CPS.

1.2.2 Renewable subsidies

Various renewable subsidies were implemented since the beginning of the 21st century. As one of the main support mechanisms for large-scale renewable electricity projects, the

[4] In the summer of 2019, the Dutch Parliament failed to pass a vote on a proposal to introduce a Dutch Carbon Price Floor.

Renewable Obligation Certificates (ROCs) were first introduced in GB in 2002, and since 2005, Northern Ireland took part in the initiative.

The ROCs obliged licenced electricity suppliers to source a certain proportion of the electricity they supply from renewable sources. The obligation, escalating yearly between 2010-2017, substantially reduced GHG emission in the UK energy generation sector. Between 1 April 2016 and 31 March 2017, 22.2% of the total electricity supplied within the UK was from renewable sources, and 28.3 $MtCO_2e$ emissions were avoided through renewable generation under the scheme (Ofgem [114]), which equals to 3.6% of the total GHG emissions in 1990.

Since 2017, the Renewable Obligation scheme has been closed to new entrances (while the existing participants remain until 2037), replaced by the Contracts for Difference (CfD) scheme introduced in the *Energy Act 2013*.

The first allocation round of the CfD scheme ran from October 2014 to March 2015. Under the CfDs scheme, a low carbon electricity generator sign a private contract with a government-owned company, and the generator is paid the difference between the "strike price" and the "reference price". The "strike price" refers to a price reflecting the cost of investing in a particular low-carbon technology, and the "reference price" refers to the market price of electricity in the GB market, such as the wholesale price. The CfDs scheme hence incentivises low-carbon investments in the electricity generation sector by providing renewable generators with a high and stable revenue stream and hedging the risks from exposure to the volatile wholesale markets.

Renewable energy generators also enjoyed other subsidies such as Levy Exemption Certificates (LECs) between 2001-2015 and Feed-in Tariffs (FiT) between 2010-2019. The LECs exempted renewable generators from paying the Climate Change Levy (CCL), an energy consumption tax, hence giving renewable generators competitive advantages in the market. The FiT scheme, on the other hand, subsidised small-scale low-carbon electricity generators by paying a "generation tariff" to whoever generates their own electricity from renewable energy technologies such as solar panels and wind turbines. Therefore, under the FiT scheme, any individual or party connected to the grid became a "prosumer" and can either consume or sell electricity.

Using the EnVision model, Ofgem [116] estimates that renewable subsidies are the second-most significant contributor to the GHG emissions reduction in the energy generation sector, reduced cumulative emissions by 235 $MtCO_2$ between 2010-2018, or 38% of total CO_2 mitigation from key decarbonisation policies (introduced in this chapter) in the energy sector. It is also worth mentioning that the scale of emissions reduction might be underestimated because, in the long run, the sector may benefit from learning-by-doing.

1.2.3 Demand-side policies

Both carbon prices and renewable subsidies are supply-side policies (except the FiT scheme, which targets on both supply and demand sides). Meanwhile, demand-side policies are also recognised as useful policy tools to achieve emissions reduction targets. Besides aiming at reducing energy demand, demand-side policies also aim to make energy demand more flexible and compatible with the growing capacity of variable renewable energy sources in the fuel mix.

Among various demand-side policies, the rollout of smart meters will play a crucial part in a future low-carbon energy system. Smart meters, some with in-house displays, automatically record and transmit households' energy consumptions to their energy suppliers on a real-time basis. It allows households to participate in dynamic tariff schemes, where electricity prices are time-varying to incentivise households to shift electricity demand from high-price to low-price periods. In Chapter 5, we estimate that dynamic tariffs bring benefits to both households and retailers if the market regulator sets specific rules which shift the market gain from retailers to consumers.

In a low-carbon energy system of the future, with over 80% of electricity coming from variable renewable energy and greater electrification of transport and heat, smart meters would be crucially important to balance supply and demand of electricity. Furthermore, the long-run effects of smart meters and dynamic tariffs cannot be ignored – they make low-carbon technologies more attractive to households and incentivise them to switch to more energy-efficient and smart household appliances.

Two other on-going demand-side policies include the Energy Company Obligation (ECO) began in April 2013 and the Renewable Heat Incentive (RHI) for domestic (1 April 2014 onwards) and non-domestic customers (15 July 2009 onwards). The ECO scheme obliges energy suppliers to promote energy efficiency measures to domestic energy users, including actions on replacing and upgrading inefficient heating systems. The RHI scheme, on the other hand, provides financial incentives to renewable heat such as solar thermal panels and biomass boilers.

Before the ECO scheme, other demand-side policies were also contributing to GHG emissions reduction. One example is the Carbon Emissions Reduction Target (CERT) that ran between 1 April 2008 and 31 December 2012. The CERT required large gas and electricity suppliers to achieve carbon emissions reduction targets from domestic premises in Britain. Another example would be the Community Energy Saving Programme (CESP) that ran from 1 October 2009 to 31 December 2012. The CESP set an overall CO_2 emissions reduction target on energy companies, and required energy suppliers and generators to deliver energy-saving measures to domestic consumers in low-income areas. In the end, the CESP achieved about 85% of its initial CO_2 emissions reduction target (Watson and Bolton [151]).

1.2.4 EU air quality Directives

Alongside the domestic policies and laws, UK emitters are also under the air quality regulations imposed by the EU. One example is the Large Combustion Plants (LCPs) Directive that entered into force on 27 December 2001. The Directive targeted power plants whose rated thermal input is equal to or greater than 50 MW, and aimed to reduce emissions of acidifying pollutants, particles, and ozone precursors. The impact of the EU air quality Directives has been substantial. Between 2004 and 2015, the EU-wide SO_2, NO_x, and dust emissions from large combustion plants were reduced by 77%, 49.5%, and 81%, respectively.[5] German et al. [71] estimate that of the observed emissions reduction, 71% of SO_2, 38% of NO_x, and 75% of dust were due to the improvement in the emission factor, driven by EU legislations.

Another example is the Industrial Emissions Directive (IED) transposed into legislation by the EU Member States in 2013. The IED aimed to reduce harmful industrial emissions across the EU via better application of the "best available techniques" – the existing techniques that are optimal for remissions reductions. At the time of writing, a backwards-looking evaluation of the IED is ongoing.[6] The expectation is that the IED would increase legislation effectiveness, improve the environment (mainly by causing the early retirement of polluting plants), and stimulate innovation.

1.3 The Decarbonisation Progresses in Other Sectors

In 2019, the UK's GHG emissions were 55% of those in 1990, on the way to the initial 2050 target of 80%.[7] The power sector has been so far the most successful sector in decarbonisation, masking the failure in other sectors.

Business sectors, in which GHG emissions mostly come from industrial, commercial, and miscellaneous combustion, are contributing the second-highest amount of emissions reduction. The reduction is mostly due to the accelerating delivery of renewable energy, benefited from initiatives such as the RE100[8] that sets a public goal for 100% renewable energy used by influential businesses by a particular year. In the near future, a new and low-carbon economy would require new business models that reflect changes in society. A good

[5] See EEA.
[6] See Thomson Reuters Practical Law
[7] See Provisional UK greenhouse gas emissions national statistics 2018.
[8] See The Climate Group.

example is the sharing economy, which refers to an economic model where people acquire, provide, and share access to goods and service that is often facilitated by a community-based on-line platform. The sharing economy would potentially lowers GHG emissions (Wosskow [160]) and grew by 60% in the 18 months between January 2016 and July 2017 in the UK (Ozcan et al. [120]).

The GHG emissions in the transport sector have been rather flat during the past decade (see Figure 1.1). However, research has shown that the electrification in the transport sector is experiencing a tipping point, where the sale of electric vehicles (EV) in the UK seems to be experiencing an exponential growth (CISL [39]). The growing share of electric vehicle on the road should have a significant effect on GHG mitigation, given the low carbon intensity of electricity. However, it is still challenging to decarbonise the aviation sector, as it is neither possible to electrify commercial air travel by 2050 nor to offset the vast amount of GHG from aviation by afforestation, although biofuels offer a potential solution if their carbon intensity can be reduced.

The residential sector also experienced limited decarbonisation progress during the past decade. Benefiting from successful decarbonisation in electricity generation, GHG emissions in the residential sector were reduced by 15% between 2008 and 2018. However, the decarbonisation in the construction (of buildings) process is still challenging. Stronger regulation approaches are advocated to boost energy efficiency in old buildings (CISL [38]) and tight standards for new buildings.

Figure 1.1 shows that in the UK between 2008-2018, the GHG emissions from the agricultural sector were stable at 45MtCO_2e/year, or about 10% of the total GHG emission in 2018.[9] The agricultural sector is considered as one of the hardest sectors to decarbonise, and stronger regulatory policies should be brought to the table, such as financial support on the emissions reduction, greater investment on emissions reduction technology, and accelerating the rate of tree planting (CCC [32]).

To summarise, heat, transport and business sectors are the next battlefields for decarbonisation. Substantially decarbonising the power sector is the foundation for the electrification of transport and business sectors. Therefore, decarbonisation in the power sector should be the top priority for most countries.

1.4 Achievements and Lessons

Besides the achievement in the environmental outcomes and the reform of the power sector, the Climate Change Act has also been successful in other areas. Fankhauser et al. [58]

[9] See GOV.UK

interviewed 33 stakeholders and experts in the field of climate change and summarised three major achievements of the Act so far.

First, the Act has transformed the political debate on climate change. The delivery of detailed reports, such as the annual reports by the CCC and the carbon budgets every five years, provide focal points on climate change-related debates. The CCC reports have become the key resource for policymakers, business stakeholders, public media, and academics to conduct policy analysis.

The second achievement is that the need for decarbonisation is now widely accepted. The UK's main political parties have invested a significant amount of political resources in the Act, lowering the risk of political back-tracking (of the Act). The carbon budgets and the CCC also establish strong guardrails against deviations from the long-term path, enabling the UK to maintain its commitments to tackle down climate change.

Finally, one of the unexpected success of the Act is that the UK has become the international leader of climate change. The Act is one of the factors that the UK played a leadership role in the negotiation of the Paris Agreement. Not only politicians but also private companies draw on the Act on the international stage of climate legislation.

However, Fankhauser et al. [58] also argue that there are still issues with the Climate Change Act. For example, the gap between the emission target and the policies designed to implement them has been widened – as discussed in Section 3, apart from its success in the power sector, the progresses in other sectors seems to have stalled. It has also been pointed out that mitigating the effects of climate change like flooding have not been effectively covered by the Act.

The Climate Change Act provides lessons to other countries, especially those who intend to legislate their GHG emissions reduction targets. Fankhauser et al. [58](p.1) summarise four key aspects that the UK's Climate Change Act brings to the international climate law-making:

> *"A comprehensive framework law is an essential tool to coordinate and advance climate action with respect to both reducing greenhouse gas emissions and climate resilience; a good climate law contains statutory targets, assigns clear duties and responsibilities and provides clarity about the long-term direction of travel; economy-wide, multi-year targets, set well in advance, help to define a clear, yet flexible path towards the long-term climate objective; a strong independent body is critically important to ensure consistent policy delivery and evidence-based decision-making."*

The decarbonisation in the power sector plays a fundamental role to achieve the long-term, ambitious emissions reduction target. Here, we summarise the UK's lessons on decarbonising power sectors.

First, among the decarbonisation policies, carbon prices and renewables support play crucial roles. A carbon price in the energy sector potentially makes coal the more expensive fuel, and newly built wind farms would then displace the more polluting coal-fired power plants instead of CCGTs. On the other hand, if the social cost of carbon is estimated to be high (which is the case in most recent literature, see e.g. Stern [143]), renewable support would bring benefit to the economy in the long-run (Cullen [45]).

Next, the rapid decline in the cost of renewable energy (Ilas et al. [84]) indicates that stable and credible policies (such as CfD and FiT) stimulate learning-by-doing. Therefore, subsidising other new but costly decarbonisation technologies such as producing hydrogen for a variety of uses including storage and generation later and Carbon Capture and Storage (CCS) could also potentially create learning-by-doing.

Third, in the future, the balancing of supply and demand will be challenging in a highly renewable power system. Besides flexible technologies such as pumped storage and storing hydrogen, demand-side policies can substantially lower balancing costs. Therefore, a long-term plan to incentivise demand response[10] is essential.

Last but not least, it is important to keep the energy bill affordable to consumers, and a competitive energy market drives down costs and prices. Although this last lesson is not directly related to decarbonisation policies, it is crucial for the redistribution of social welfare. In 2016, an average household used 4% of their total expenditure on energy, raised from 3% in the early 2000s. For households in the bottom 10% of the income distribution, the number increases to 8.4% (relative to less than 6% in the early 2000s).[11]

1.5 Targeting on net zero

Despite the aforementioned achievements in decarbonisation, the CCC [32] estimates that the UK is not on track to its 2023 decarbonisation commitment in the fourth (2023-2028) carbon budget. Hence it urges the government to set clear, stable, and well-designed policies. The CCC also recommended that it was feasible, cost-effective, and necessary for the UK to set a “net zero” GHG emissions target by 2050. In June 2019, the UK’s Parliament passed legislation targeting to reduce the GHG emissions to "net zero" by 2050. This has made the UK the first major economy to target on a zero-carbon future.

Net zero, also known as "carbon neutrality", seeks to completely offset the emitted GHGs via natural carbon sinks such as oceans and forests, and artificial carbon sinks such as CCS

[10] Balancing supply and demand from the demand side.
[11] See Ofgem.

systems for biomass. The target covers all sectors of the economy, including international aviation and shipping that were initially ignored.

The net-zero target is considered to be a great opportunity for the power sector because completely decarbonising the sector is essential for achieving this target. This would require the government to develop a highly renewable power system. In a pathway to achieving a net-zero power sector, the UK government has set a goal to deploy 40 GW of offshore wind by 2030.[12]

In simulating the UK power system beyond 2030, the National Infrastructure Commission (NIC [106]) demonstrates that a power system relying on renewables and flexible technologies such as hydrogen-powered generation could be substantially cheaper (by 30%) than a power system that relies heavily on nuclear power plants (such as the current situation where nuclear power plants contribute about 20% of the UK's annual electricity supply). On the other hand, the development of CCS enables bioenergy to displace nuclear power stations and generate baseload.

The net-zero target cannot be achieved by the power sector alone. Policies targeting on efficient buildings and low-carbon heating, EV markets, CCS clusters, afforestation and peatland restoration, as well as low-carbon farming facilities must be ramped up significantly and delivered with far greater urgency. That means strong government leadership is required, and support from businesses and communities is also needed.

1.6 Conclusion

The UK's Climate Change Act so far has been of a great success, especially in decarbonising the power sector. The UK's experience brings valuable lessons to other countries, especially those who have not yet legislated a carbon reduction target by a certain year.

The UK is also among the first countries to set a net-zero target, which would require it to fully decarbonise the energy sector and then electrify (most) other sectors to take advantage of the low carbon intensity of electricity. This indicates that the power sector is playing a central role in achieving carbon emissions reduction targets.

It is also worth noticing that carbon mitigation does not necessarily conflict with economic growth. From 2009 to the end of 2019, the UK's GDP has grown by 20%, while its total GHG emissions have been reduced by 32%. Although one may argue that the UK's GDP growth could be even higher without the emissions reduction target, BEIS [15] shows that between 1990-2016, while the emissions reduction in the UK (42%) has been fallen at a

[12] See renews.

much higher rate than other G7 countries (3% on average), the UK's GDP is growing at a faster rate (67%) than others (61%).

Chapter 2

The Impact of a Carbon Tax on the CO_2 Emissions Reduction of Wind

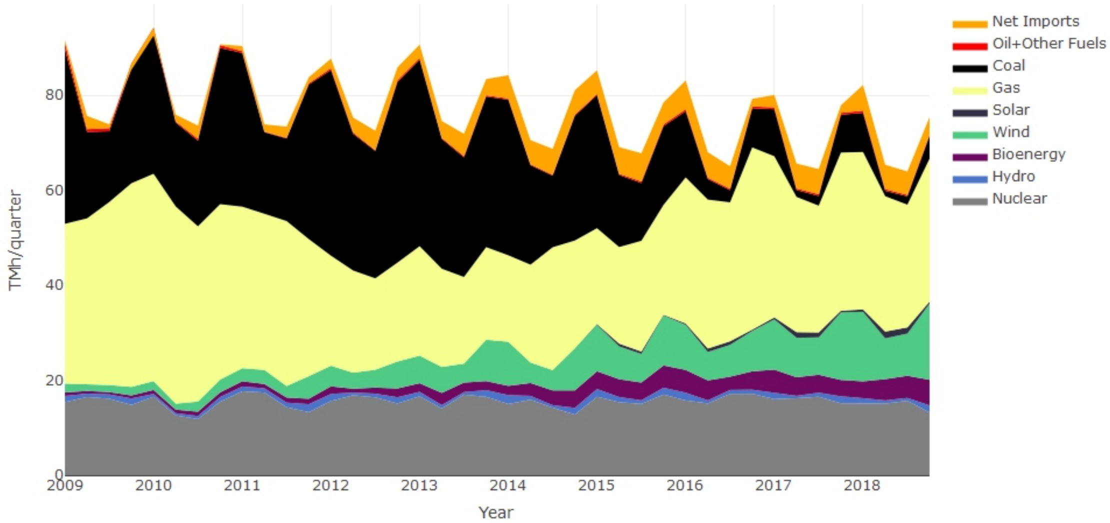
2.1 Introduction

Energy policy aims to reduce emissions at least long-run cost while ensuring reliability. Policies to support wind or solar panels electricity (PV), improve efficiency, or shift peak demand need to be assessed on the cost of the emissions reduced. Ofgem [115] in its *State of the market 2018* is a good example, comparing the cost effectiveness of various UK energy policies. This chapter shows how to estimate CO_2 reductions in electricity from wind deployment in both the short and long run. Both need to be estimated to adequately measure carbon savings. The chapter shows how to measure these savings.

We demonstrate this by measuring the CO_2 displaced by wind in Britain as the price of carbon varies. The UK Government introduced a Carbon Price Floor from 2013. This takes the form of a carbon tax (the Carbon Price Support, CPS) on fuels used to generate electricity. The CPS is added to the EU Allowance (EUA) price to give the total extra cost of the carbon content of fossil fuels. By 2015 this was sufficiently high to dramatically impact the fuel mix in generation, as shown in Figure 2.1. The share of coal fell from 41% in 2013 to 6% in 2018. Great Britain[1] therefore offers an excellent test-bed for the impact of a carbon tax (the CPS) as the fuel mix is likely to affect the carbon displaced by wind. Wind is hard to forecast with much accuracy day-ahead when the time comes to decide which types of generation to commit and run. As wind varies from moment to moment, the carbon displaced will depend on the plant operating and its flexibility. We study this short-run impact econometrically to find the main drivers of the short-run displacement achieved.

[1]Northern Ireland was exempt from the CPS as it forms part of the Single Electricity Market with Ireland, who declined to adopt a Carbon Price Floor.

Fig. 2.1 GB generation per quarter by fuel type (legends order the same as fillcolours)



Source: Elexon Portal

Policies are chosen for their long-run impact. Governments set targets for the future share of renewable electricity and carbon budgets. These policies will affect the future fuel mix, and hence the dispatchable plant available daily. We determine this long-run impact with a unit commitment dispatch model of the 2015 GB system. We examine the effect of increasing wind capacity by varying amounts up to 25%. Long run has the conventional meaning that it is a period over which wind capacity can change, in contrast to the short run in which wind capacity is fixed but its output varies. We study the impact of the CPS in 2015. The first counterfactual has no CPS, but just the EUA price. The second looks to the CPS in 2018 after the EU Emissions Trading System was reformed, which raised the GB carbon price substantially above its 2015 level.

This chapter argues that policies to reduce emissions require an analysis of both the short-run and long-run impacts. Increased wind capacity raises the expected amount of wind generation, which can be estimated using a deterministic unit commitment model. After plant has been committed, realised wind and demand will likely differ from forecast. Committed plant will need to adjust their output. These responses are better captured by a short-run econometric model that also reflects actual behaviour in a liberalised market that may differ for various reasons from an efficient centrally dispatched system.

The Marginal Displacement Factor (MDF) measures the CO_2 reduced by an extra 1 MWh of wind, which depends on the plant mix and fuel and carbon prices. The MDF of renewables will therefore vary over countries and time. The MDF is useful for determining the extra support to offer low-carbon technologies if the market price of carbon is below its social cost. It can be (and is) also used to measure the cost-effectiveness of carbon policy interventions.

The econometric estimates also give the short-run Marginal Emission Factor (MEF) of demand — the change in emissions resulting from a change in demand of 1 MWh (tonnes CO_2/MWh). This can be used to estimate the impact of carbon prices on wholesale prices.

The next section briefly reviews related literature before describing the British Carbon Price Floor and developments in the EU Emissions Trading System, their impact on GB carbon prices over time and the evolution of GB fuel costs. Section 2.4 summarises the merit order effect to motivate wind MDF's dependence on relative fuel costs. Section 2.6 derives the SR-MDF of wind; Section 2.7 measures the LR-MDF. Section 2.8 contrasts the SR and LR-MDFs and discusses their use in policy analysis. Section 2.9 concludes.

2.2 Literature review

We have only found one *ex post* econometric analysis (Staffell [142]) of the performance of the GB CPS — even though Britain's CPS has been in place for over five years. Staffell [142] explains why CO_2 emissions fell by 46% in the three years to June 2016, whereas our aim is to explore the underlying mechanism driving changes in the MDF. The econometrics also identifies the marginal price-setting plant, which can be compared with the increase in the GB electricity prices from CPS, to estimate the CPS cost pass-through to the GB electricity prices (see Chapter 3).

Our SR-MDF estimates overlap the period that Thomson et al. [147] studied econometrically (2009-2014). They find that in 2010, a period of intermediate coal costs, the MDF was 0.61 tCO_2/MWh. Counterintuitively, this fell to 0.48 tCO_2/MWh in 2014 (when the CPS was introduced, although at a low level) when coal became more expensive. We aim to better understand these changes in the MDF, which Thomson et al. [147] note might be due to the "unusual operation of the system in 2012-14". We confirm Thomson's findings and show the reason for the apparently counter-intuitive findings.

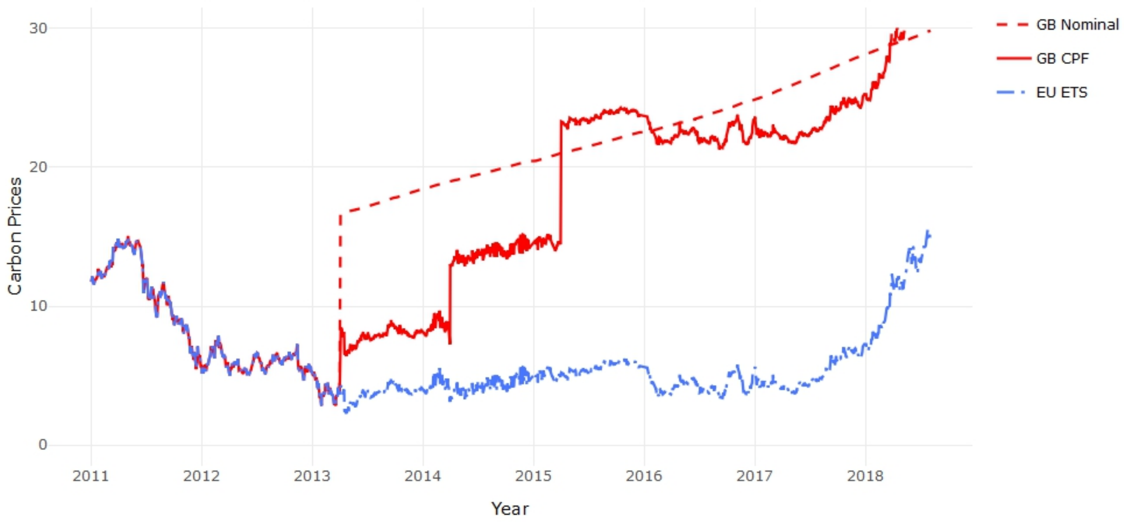
Most studies make "instantaneous" CO_2 emissions as the dependent variable in regressions (Wheatley [154], Thomson et al. [147], Kaffine et al. [87], Novan [110], Callaway et al. [27]). Instead we use half-hourly coal and gas generation as dependent variables and develop non-linear econometric models to estimate the marginal fuel (coal and gas, MWh) displacement per MWh of wind and its dependence on the fuel cost difference. Staffell [142] and Cullen [45] also use coal and gas generation as dependent variables but study the impact in more parsimonious linear forms. Our non-linear estimates provide wind's MDF. The conventional approach estimates MDFs directly. Our indirect estimate has two advantages. First, it explains the underlying mechanisms that drive the dynamics of the MDF. Second, it allows us to study counterfactuals without the CPS and with higher carbon prices, which would be difficult without knowing the underlying mechanisms.

The CPS raises coal variable cost more than CCGTs, potentially changing the merit order. Similarly, Cullen and Mansur [46], Fell and Kaffine [63], and Brehm [23] find that carbon taxes or low gas prices reduce emissions by displacing coal.

2.3 The British Carbon Price Floor

The Carbon Price Floor (CPF) was announced in the 2011 Budget to come into effect in April 2013. It was intended to raise the price of carbon in the GB electricity supply industry to £(2011)30/tCO_2 by 2020 (the dashed line at current prices in Figure 2.2) and £(2011)70/tCO_2 by 2030, sufficient to make mature zero-carbon generation competitive. The CPF adds the Carbon Price Support (CPS, a carbon tax added to the EUA price) on electricity fuels. The CPS was originally set at £4.94/tCO_2. By April 2013, the EUA price had fallen to just under £4/tCO_2 so the effective price was far below the desired level (Figure 2.2). The CPS was raised in 2014 to £9.55/tCO_2 and again in 2015 to £18.08/tCO_2, to bring the price back to the desired CPF trajectory.

Fig. 2.2 Evolution of the European Allowance (EUA) price and CPF, £/tCO_2

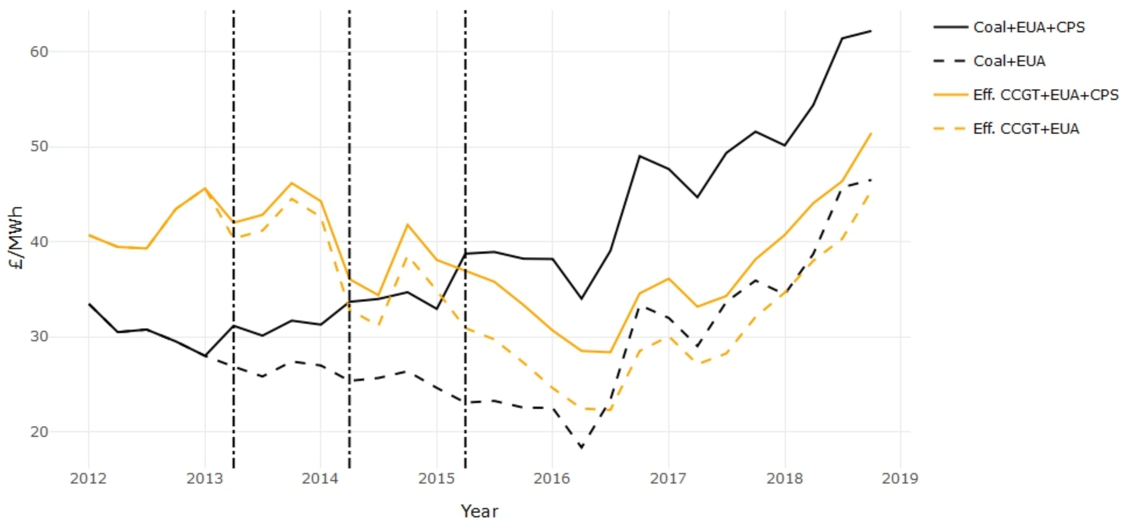


Source: investing.com

Initially the UK Government hoped that other EU countries would be attracted by this fiscally appealing solution to the politically intractable problem of ETS reform. Other EU Member States declined to follow (until recently when the Dutch Government announced plans for a CPF). Faced with a potentially large mismatch between the cost of generating electricity in Britain and on the Continent, the Chancellor froze the CPS at £18/tCO_2 from 2016-17 through 2020-21.[2] Figure 2.2 shows the increasing divergence between the EU and GB CO_2 prices. In November 2017 the EU finally agreed to reform the ETS, introducing a Market Stability Reserve that allows surplus EUAs to be cancelled (Newbery et al. [104]). Figure 2.2 shows the EUA price sharply rising, taking the GB price above the original CPF trajectory.

The impact has been dramatic. Figure 2.3 shows the variable fuel costs from 2012-18, with and without the CPS. It was not until April 2015, when the CPS was almost doubled, that the variable coal cost rose above the variable cost of more efficient CCGTs. Figure 2.1 shows the resulting massive switch from coal to gas.

Fig. 2.3 Electricity generation cost by fuels for generators



Source: BEIS *Quarterly Energy Prices*

The rest of this chapter quantifies the impact of the CPS on the carbon savings from wind, which, as Figure 2.1 shows, has been increasing rapidly.[3] We estimate both the short-run

[2]See the document from the House of Commons.

[3]The same approach could in principle be applied to carbon savings from solar PV or smart charging of battery electric vehicles, but the necessary data are not currently readily available.

(SR) and long-run (LR) Marginal Displacement Factors (MDFs). The short-run impacts are studied econometrically over a period of varying fuel and CPS prices and varying plant mix and wind capacity, providing statistically highly significant estimates of the short-run impact of wind. We use an hourly unit commitment dispatch model of British electricity (described in Chyong et al. [37]) to compute the long-run impact of the CPS. Wind capacity is increased by 25%, leaving the plant mix and fuel prices constant, and varying the level of the CPS. We expect the short-run MDF (SR-MDF) to differ from the long-run MDF (LR-MDF), as the SR-MDF estimates the impact of variable (imperfectly predicted) wind on generation given the *existing* wind capacity. The LR-MDF considers a deterministic world over the plant commitment horizon in which the known increase in wind capacity leads to an accurately forecast wind output. Plant is efficiently scheduled to meet accurately predicted residual demand. The two estimates may differ for various reasons discussed below. Both estimates are needed to inform policy.

Table 2.1 gives thermal efficiencies and emissions.[4] Coal has more than twice the carbon intensity of gas. A CPS of £18/tCO_2 raises the marginal coal cost by £15.7/MWh$_e$ and efficient CCGTs by £6/MWh$_e$, reducing the relative cost of gas by nearly £10/MWh$_e$. (The average baseload price from 2011-13 was £47/MWh$_e$).

Table 2.1 Characteristics of GB fuel types

	Fuel Price £/MWh$_{th}$	Capacity GW	Efficiency GCV	CO_2 t/MWh$_e$
Coal	£6.57	17.1	35.6%	0.871
CCGT new	£15.87	14.2	55.1%	0.333
CCGT older	£15.87	5.2	52%	0.352
CCGT oldest	£15.87	7.6	36%	0.511

Note: GCV is Gross Calorific Value (Higher Heat Value), subscripts $_{th}$ refer to thermal content, $_e$ electric output. Efficiencies are often quoted for the more impressive Lower Heat Value. For gas the LHV is 90% of the HHV, downgrading the 61.2% nominal efficiency to 55.1% HHV. The oldest CCGTs are often running inefficiently part-loaded or in open-cycle mode for fast balancing response.

Figure 2.3 shows the coal cost first exceeded efficient CCGT costs in Q2 2015. Before then, the dark green spread (the average wholesale prices *less* the coal cost including the EUA *plus* CPS) was £7.7/MWh$_e$ while the clean spark spread (average wholesale prices *less* the cost of CCGT including carbon cost) was £3/MWh$_e$, making coal the preferred base-load and gas the mid-merit plant. From November 2015 to June 2017 the dark green spread fell to -£1.8/MWh (a loss running all the time, but higher priced hours would still give a positive

[4] See Statista.

spread), while the average clean spark spread rose to £8.9/MWh, shifting gas from mid-merit to base load, and coal to mid-merit or peaking load.

Coal has normally been the major swing fuel in winter months, and indeed on a cold winter day (09:30 February 27, 2018) CCGTs were producing 19.4 GW but coal was producing 11.1 GW, its maximum.[5] On a calm sunny summer day (15:40 August 3, 2018), CCGTs were producing 17.8 GW, coal only 0.5 GW, wind down to 1.1 GW and solar up at 4.8 GW.

2.4 The Merit Order Impact of Carbon Pricing

Renewables (wind, solar PV, and run-of-river hydro) and nuclear power have zero variable carbon emissions and low variable costs, so if available, they will displace more expensive fossil generation. The merit order for conventional (dispatchable) plant ranks plant in increasing variable cost, with residual demand (total demand less renewable generation) determining the marginal conventional plant displaced by renewables. Exactly which fossil generation will be displaced depends on their position in the merit order but also on which are able to adjust their output. The static merit order impact of renewables *capacity* in displacing fossil plant is well-understood (Clò et al. [40], Cludius et al. [41], Deane et al. [49], Green and Vasilakos [74], Ketterer [89]). The impact of variations in renewable *output* needs attention to plant dynamics.

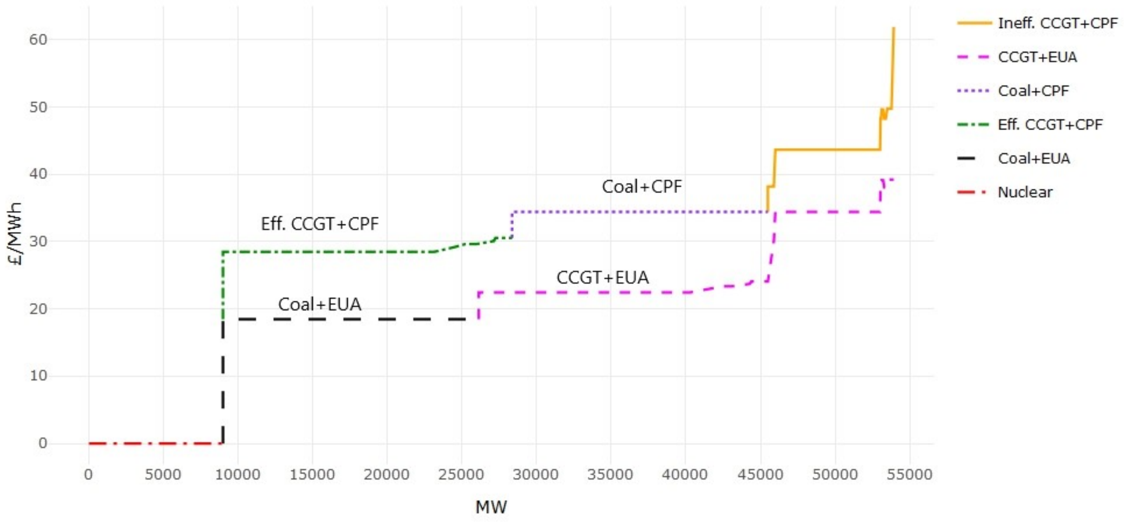
Figure 2.4 shows the Q2 2016 merit order of GB nuclear, coal and CCGT plant (excluding biomass, combined heat and gas (CHP), pumped storage, interconnectors and renewables) with either just the EUA or with the added CPS at £18/tCO_2. At EUA carbon prices coal is cheaper than all CCGTs. With the CPS, efficient CCGTs displace coal, but that is still cheaper than the less efficient CCGTs, some of which are potentially operating as balancing units in open-cycle mode.

Figure 2.5a shows the half-hourly generation by fuel types in two consecutive days in January 2017. Exports are shown as negative imports and pumped storage either is a negative generation (when pumping) or positive. The negative amount is subtracted from the stable nuclear output, so negative nuclear implies that pumping demands power.

The horizontal lines in Figure 2.5b show the marginal costs of generating with gas in high efficiency CCGTs, including carbon at £18/tCO_2, the middle one is coal and the higher

[5] Real time data are available from Gridwatch; the installed capacity for coal was 11.1 GW in 2017 (instead of the value of 17.1 GW in 2015 in Table 2.1), see the Transparency Platform. One further reason for the significant reduction in coal capacity is because the Large Combustion Plant Directive required expensive refurbishment causing some generators to close coal-fired capacity in the years leading up to 2016.

Fig. 2.4 Merit order for conventional generation plant, Q2 2016



Source: Fuel prices from BEIS Table 3.2.1; thermal efficiency and capacity for fossil fuel plants from DUKES.

the least efficient CCGT , with peaking open cycle gas turbines in the upper tail in Figure 2.4. Figure 2.5b also plots the spot market prices and coal and gas generation for the two days.

The vertical lines in Figure 2.5 show where coal changes from having a negative dark green spread to positive or *vice versa* (where the spot market prices intersect with the coal cost). Coal plant is costly to restart, so if needed later will run at minimum load, and ramp up to deliver when demand and prices rise. Wind varies between 6.7 GW and 4.3 GW but this variation is dwarfed by demand varying from 25-49 GW. Coal and gas generation follow load and any adjustment in response to wind variations are swamped by load variations. However, while load is reasonably predictable, wind is less predictable and likely to rely more on the balancing market, for which flexible plant is at a premium (Thomson et al. [147]).

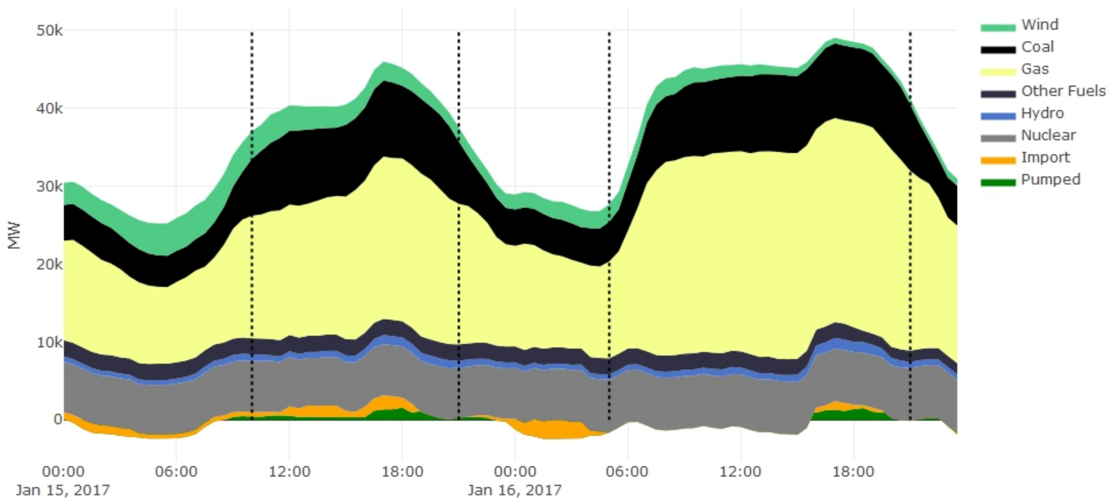
2.5 Data

The values for the Carbon Price Support (CPS) are published by the Government HoC [80]. The carbon content of natural gas is well-defined at 0.1839 tCO_2/MWh_{th}, and the carbon intensity for coal is 0.310 tCO_2/MWh_{th} from DECC's *Greenhouse gas reporting - Conversion factors*. Table 2.2 gives the carbon prices used.

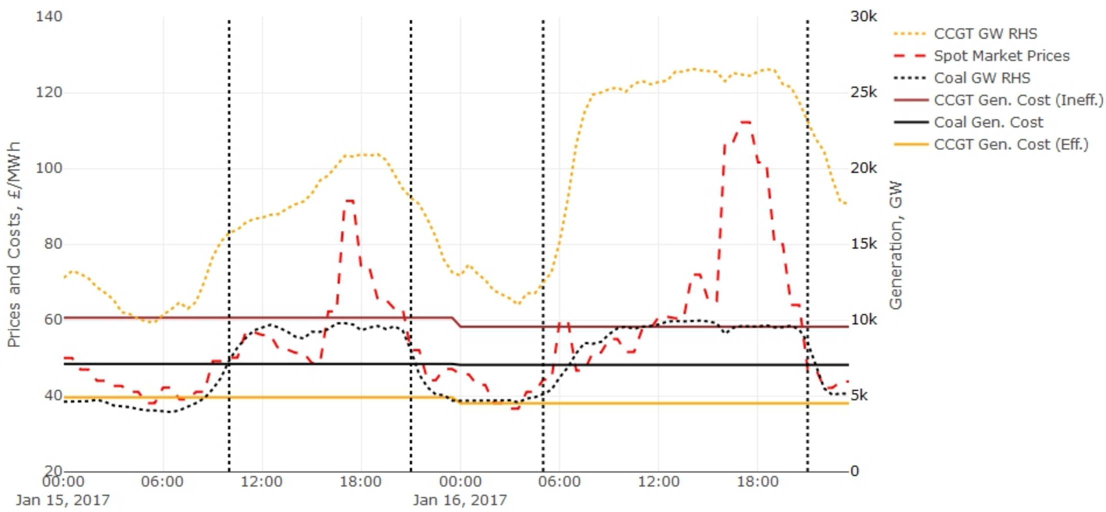
The quarterly prices of fuels into power stations are published by the Department for Business, Energy, and Industrial Strategy (BEIS, previously by the Department of Energy

Fig. 2.5 Generation, prices and costs by half-hour, 15-16 Jan 2017

(a) Half-hourly output (legends order the same as fillcolours)



(b) Half-hourly spot market prices and generation costs



Source: Elexon Portal

and Climate Change, or DECC) as Table 3.2.1 and give gas and coal prices per kWh$_{th}$. Both include delivery and other costs from the spot prices (National Balancing Point (NBP) for gas, various for coal but often the Rotterdam Coal Futures (ARA) west Europe prices).

Table 2.2 CPS rates in fiscal years beginning

	01/04/2013	01/04/2014	01/04/2015	01/04/2016
gas /MWh$_{th}$	£0.91	£1.75	£3.34	£3.31
coal /MWh$_{th}$	£1.59	£2.95	£5.65	£5.57
CPS £/tCO2	£4.95	£9.52	£18.16	£18.00

Source: Climate Change Levy Rates

The gas price is less constant than the coal price as coal is more illiquid and storable, while the fuel prices published by BEIS only varies quarterly. It is fine to use quarterly prices but prices at higher frequency would provide more variation hence smaller standard errors on the estimates. Therefore, the daily spot natural gas futures price is downloaded from the InterContinental Exchange,[6] which is the same as the NBP gas price; we then average the daily spot price by years and quarters, and take difference between the BEIS quarterly prices and the quarterly averaged spot prices to calculate the delivery and other costs for each quarter of each year; finally, we top up the daily spot price by the delivery and other costs and obtain the daily gas price, which includes delivery and other costs. The daily coal price is obtained by smoothing the BEIS quarterly coal price to avoid sudden rises and falls at the border of two consecutive quarters.

The average thermal efficiency for coal-fired power plants is fixed at 35.6%, and the *weighted* (by capacity) average thermal efficiency for efficient CCGTs is fixed at 54.5% (ranging from 51.4% to 55.1% for efficient CCGTs). Given this, the carbon emission factor for coal is

$$0.31(\text{tCO}_2/\text{MWh}_{th}) \div 0.356 = 0.871(\text{tCO}_2/\text{MWh}_e),$$

and for efficient CCGTs is

$$0.1839(\text{tCO}_2/\text{MWh}_{th}) \div 0.545 = 0.337(\text{tCO}_2/\text{MWh}_e).$$

Then the generation costs for coal and efficient gas are respectively calculated using the formula:

$$\text{Generation Cost} = \text{Fuel Price} \div \text{Thermal Efficiency} + (\text{CPS} + \text{EUA}) \times \text{Emission Factor}.$$

The data for half-hourly generation by fuel type were downloaded from the Elexon Portal. For each year there are some (half-)hours with misrecorded data. Specifically, whenever the CCGT generation is lower than 1000 MW, we treat it as misrecording and replace it by

[6] See InterContinental Exchange.

"NA"; we also remove the data where the half-hourly change in total electricity supply is above 3000 MW - this ensures the removal of most outliers.

The EUA prices are downloaded from investing.com[7] and are converted to GBP using the exchange rate from the same data source.[8]

2.6 Econometric Analysis

The short-run marginal displacement factor (SR-MDF) measures the marginal CO_2 savings of wind with the *existing* wind capacity from 2012-17. This covers the period before the implementation of the CPS (pre Q2 2013), the period when it was implemented and raised twice (Q2 2013 - Q2 2016) and when it is fixed at £18/tCO_2 (post Q2 2016). Thomson et al. [147] estimate the SR-MDF from 2009-14. Our data overlaps their period, providing a credibility check.

The SR-MDF can barely be estimated via a back of the envelope estimate method by simply averaging the emission factors of coal and gas plants. Instead, the SR-MDF is an weighted average of the emission factors and without investigating which fuel type responds to wind, we are unable to identify the weights. In this section, we describe the econometric methods that estimates the weights, which are then used to estimate the SR-MDF.

2.6.1 The short-run impact of wind

The conventional approach to estimate the SR-MDF (Hawkes [76], Thomson et al. [147], Staffell [142]) uses the following model:

$$\Delta E_t = a\Delta D_t + b\Delta W_t + c_t + u_t, \tag{2.1}$$

where ΔE_t is the half-hourly first difference of the system CO_2 emissions (tCO_2), and ΔD_t (MWh) and ΔW_t (MWh) are the first differences of electricity demand and wind output respectively. Coefficient a is the marginal emission factor (MEF) (tCO_2/MWh) of demand and $-b$ is the SR-MDF (tCO_2/MWh) of wind. c_t is other system effects which can be half-hourly specific, and u_t is an unobserved error term.[9]

By definition,

$$\Delta E_t = e_C\Delta C_t + e_G\Delta G_t + e_O\Delta O_t, \tag{2.2}$$

[7] See investing.com.

[8] See investing.com

[9] Most related research uses unit-level data to capture unit heterogeneity. We show that a much cruder dataset gives qualitatively similar results.

where C_t, G_t and O_t are electricity generated from *C*oal-fired stations, *G*as (CCGTs) and *O*ther energy sources; e_C, e_G and e_O are the CO_2 emission intensities for coal, gas (efficient CCGTs) and other fuel sources. O_t consists of energy sources which are negligible (open-cycle gas turbines and oil), must-runs (combined heat and power and biomass), and imports, which do not count as GB sources of emissions.[10] Therefore, $e_O\Delta O_t$ is close to zero because either $e_O = 0$ (for imports) or $\Delta O_t \approx 0$ (for the must-run and negligible energy sources).

Pumped Storage (PS) charges off-peak using mostly fossil generation to generate during high price hours and provide fast reserve (available within 1 minute). If residual demand increases, replacement supply is needed. Given that PS required earlier fossil generation there is an obvious question of its carbon content. However, PS provides arbitrage, balancing and ancillary services to the extent of its capacity, regardless of wind output that primarily affects timing, and will not vary with wind output. Although PS output responds to changes in wind, its effective MDF is zero.

Substituting ΔE_t in (2.1) by (2.2) suggests the following regressions:

$$\Delta C_t = \alpha_0 + \alpha_1 \Delta W_t + \alpha_2 \Delta D_t + \boldsymbol{\theta' X_t} + \varepsilon_t, \tag{i}$$

$$\Delta G_t = \beta_0 + \beta_1 \Delta W_t + \beta_2 \Delta D_t + \boldsymbol{\delta' X_t} + \mu_t, \tag{ii}$$

where $\boldsymbol{X_t}$ is a vector of half-hourly dummy variables. First differences means that we do not need to worry about non-stationary processes.[11] Consequently, we have:

$$e_C\alpha_2 + e_G\beta_2 \approx a = \text{MEF},$$

$$-(e_C\alpha_1 + e_G\beta_1) \approx -b = \text{SR-MDF}.$$

The SR-MDF is estimated indirectly from regressions (i) and (ii) instead of (2.1). This indirect approach identifies the underlying drivers of the dynamics of the SR-MDF (i.e. the shares of coal and gas displaced by wind). Second, the non-linear version of (i) and (ii) discussed below allows us to study different counterfactual carbon prices. Staffell [142] uses a similar linear approach, finding that only fossil plant and imports adjust output to wind changes, supporting our two-step estimation. As wind supply depends on wind speed, ΔW_t

[10] Nuclear, solar, wind, run-of-river hydro are not included in (2.2) because none of them generates GHG.

[11] One may also argue that the error terms between (i) and (ii) are negatively correlated because if one unit is unavailable to meet a given level of demand, another unit might take over, suggesting a preferable Seemingly Unrelated Regression (SUR). However, when the covariates between the two regressions are exactly identical, the SUR estimates is equivalent to the equation-by-equation Ordinary Least Squares (OLS) (Takeshi 144, p.197). This also applies to the non-linear regressions below.

can be treated as exogenous. As the half-hourly domestic demand is price-inelastic (Clò et al. [40]), ΔD_t is also treated as exogenous.

The slope coefficients α_1 and β_1 are the marginal *fuel* displacement of wind, measuring the changes in coal and gas generation caused by a wind change, conditional on the change in demand and time dummies. We expect both $\hat{\alpha}_1$ and $\hat{\beta}_1$ to be negative, and $|\hat{\alpha}_1 + \hat{\beta}_1|$ to be close to but smaller than 1 — as a proportion of wind changes can be compensated by imports and pumped storage. The coefficients α_2 and β_2 measure the response of coal and gas generation to demand changes. We again expect both $\hat{\alpha}_2$ and $\hat{\beta}_2$ to be positive and $|\hat{\alpha}_2 + \hat{\beta}_2|$ to be less than 1.

The magnitudes of α_1 and β_1 depend on total energy demand (hence the time of the day) as well as the actual merit order between coal and gas, which is determined by $PD_t \equiv P_t^C - P_t^{G^e}$, the difference in variable coal (P_t^C) and efficient CCGT costs ($P_t^{G^e}$) (hereafter the cost differential).[12,13] Each day is separated into two periods: off-peak (23:00-07:00) and peak (07:00-23:00)[14] From Figures 2.4 and 2.5, the base-load plant is sufficient for energy demand during (most of the) off-peak hours and the mid-merit plant is the marginal fuel for (most of the) peak hours.[15,16] We further split the two sub-samples into $PD_t < 0$, (COAL-BASE) and $PD_t \geq 0$ (GAS-BASE) depending on which fuel is expected to run on base load, and run regressions (i) and (ii) on each sub-sample. (Data sources are in Section 2.5.)

The results are shown in Table 2.3. All estimates for the coefficients of ΔW_t and ΔD_t are statistically significant at the 0.1% level, and their signs follow our initial intuition. Specifically, during off-peak periods it is normally the base-load plant that responds to changes in wind supply and/or electricity demand. Table 2.3a shows that when coal is the base load, coal responds more strongly to wind and demand changes — if ΔW_t increases by 1 MW, ΔC_t would on average drop by 0.52 MW while ΔG_t would on average only drop by 0.41 MW. This changes when PD_t becomes positive — a 1 MW increase in ΔW_t will only reduce ΔC_t by 0.15 MW, much less than the 0.75 MW reduction in ΔG_t. The story is similar for the impact of ΔD_t on ΔC_t and ΔG_t when coal supplies the base load, where a 1 MW increase in ΔD_t would increase ΔC_t by 0.42 MW and ΔG_t by 0.55 MW. However, when gas supplies the

[12]Because inefficient CCGT plants only count for a small proportion of energy supply and only supply energy in very cold winter days, we only consider the cost differential between coal and efficient CCGT (gas) plants.

[13]We use daily gas prices, smoothed quarterly coal prices, and daily EU ETS prices to calculate the cost differential. Details in Section 2.5. Coal and gas costs are invariant within days.

[14]The definition on peak and off-peak is from Npower based on London, Eastern and East Midlands. The results are not sensitive to changing the peak period to 08:00-23:00 or 07:00-22:00.

[15]In Figure 2.4, the boundary between base load and mid-merit load in GB should be slightly above 30GW, after taking CHP, biomass, and renewables into consideration.

[16]This is the case for 2012-2017, when solar PV is on average lower than 1 GW. With significant solar, one can separate the data base on the residual demand instead of time of the day, but that will complicate interpretation and the post-estimate counterfactual application.

Table 2.3 Estimation results from linear regressions (i) and (ii)

(a) Off-peak period (23:00-07:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
(Intercept)	-5.19	-11.11^{*}	18.01^{*}	17.23^{*}
	(8.87)	(5.51)	(8.38)	(8.24)
ΔW_t	-0.52^{***}	-0.15^{***}	-0.41^{***}	-0.75^{***}
	(0.02)	(0.01)	(0.02)	(0.01)
ΔD_t	0.42^{***}	0.20^{***}	0.55^{***}	0.74^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Time Dummies	YES	YES	YES	YES
R^2	0.66	0.51	0.79	0.87
Obs.	17441	17062	17441	17062

(b) Peak period (07:00-23:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
(Intercept)	251.22^{***}	-130.50^{***}	-115.21^{***}	180.63^{***}
	(9.83)	(8.28)	(12.53)	(11.68)
ΔW_t	-0.15^{***}	-0.15^{***}	-0.66^{***}	-0.65^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
ΔD_t	0.14^{***}	0.21^{***}	0.64^{***}	0.61^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Time Dummies	YES	YES	YES	YES
R^2	0.49	0.50	0.85	0.84
Obs.	34830	34072	34830	34072

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

base load, a 1 MW increase in ΔD_t would only increase ΔC_t by 0.20 MW while increasing ΔG_t by 0.74 MW.

From Table 2.3b, during peak periods, the magnitude of changes in the coefficients of ΔW_t for coal is negligible. Gas has always been dominant in responding to wind changes during peak periods — a 1 MW increase in ΔW_t is on average accompanied by a 0.66 MW fall in ΔG_t when coal is the base load, and by a 0.65 MW fall otherwise. This might be because demand is high and more variable during peak periods; therefore flexible gas plants are better able to adjust to wind variations. In off-peak periods when coal provides the base load, CCGTs are likely to run at their minimum stable output and hence have limited ability to respond to an increase in wind supply.[17]

2.6.2 The role of generation cost differentials

Previous subsection suggests that the impacts of ΔW_t and ΔD_t on ΔC_t and ΔG_t depend on the cost differential (PD_t), especially for off-peak periods.[18] We expect this dependency to be non-linear:

$$\Delta C_t = \alpha_0 + f(PD_t)\cdot\Delta W_t + k(PD_t)\cdot\Delta D_t + \boldsymbol{\theta' X_t} + \varepsilon_t, \tag{iii}$$

$$\Delta G_t = \beta_0 + g(PD_t)\cdot\Delta W_t + l(PD_t)\cdot\Delta D_t + \boldsymbol{\delta' X_t} + \mu_t, \tag{iv}$$

where $f(PD_t)$, $k(PD_t)$, $g(PD_t)$, and $l(PD_t)$ are fourth degree polynomial functions of PD_t, selected using the Bayesian Information Criterion (BIC)[19]:

$$f(PD_t) = \alpha_{1,0} + \alpha_{1,1}PD_t + \alpha_{1,2}PD_t^2 + \alpha_{1,3}PD_t^3 + \alpha_{1,4}PD_t^4.$$

Regressions (iii) and (iv) are more robust and make more sense of the varying sensitivity of the merit order to the cost differential.

We expect the *magnitudes* of $f(PD_t)$ and $k(PD_t)$ during off-peak periods to decrease with PD_t. As coal cost increases relative to gas, coal will be less sensitive to changes in wind and total demand in off-peak periods, as it is moved off from base load. Furthermore, PD_t is expected to have its highest influence close to zero, the tipping point that determines the base-load fuel. Therefore we expect the slopes of $\hat{f}(PD_t)$, $\hat{k}(PD_t)$, $\hat{g}(PD_t)$, and $\hat{l}(PD_t)$ to be the highest around $PD_t = 0$. Similarly, the *magnitudes* of $g(PD_t)$ and $l(PD_t)$ off-peak should increase with PD_t, with the highest slopes at $PD_t = 0$.

In peak periods, we expect PD_t to have negligible impact on $\hat{f}(PD_t)$, $\hat{g}(PD_t)$, $\hat{k}(PD_t)$ and $\hat{l}(PD_t)$ as gas provides flexible response regardless of the cost difference.

The detailed estimation results are shown in Appendix A.1. The non-linear partial effects of ΔW_t on ΔC_t and ΔG_t (i.e. $\widehat{\partial\Delta C_t/\partial\Delta W_t}$ and $\widehat{\partial\Delta G_t/\partial\Delta W_t}$) and the corresponding

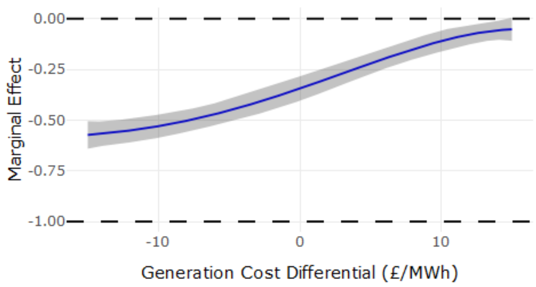
[17] In spite of the negligible change in the coefficients of ΔW_t, the direction of changes in the coefficients of ΔD_t still suggests that as coal becomes more expensive (from COAL-BASE to GAS-BASE), coal shifts to mid-merit. Specifically, during peak periods, a 1 MW change in energy demand is on average accompanied by a 0.14 MW change in coal generation when coal is the base load but by a 0.21 MW change otherwise.

[18] We find no evidence of an asymmetric partial effect when wind rises and falls ($\Delta W_t > 0$ *v.s.* $\Delta W_t \leq 0$), and demand increases and declines ($\Delta C_t + \Delta G_t > 0$ *v.s.* $\Delta C_t + \Delta G_t \leq 0$). Running regressions separately for weekdays and weekends does not change the story. See Appendix A.1.

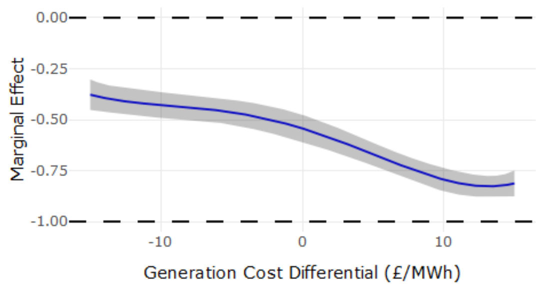
[19] The test for the joint significance of the polynomial terms are all statistically significant at the 0.1% level. For example, in $f(PD_t)$, the null hypothesis is $\alpha_{1,1} = \alpha_{1,2} = \alpha_{1,3} = \alpha_{1,4} = 0$.

Fig. 2.6 The estimated partial effects of ΔW_t on ΔC_t and ΔG_t, regressions (iii) and (iv)

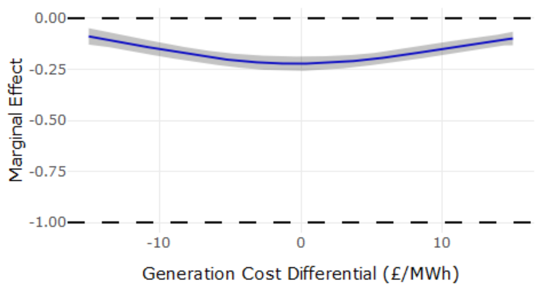
(a) partial effects of ΔW_t on ΔC_t, off-peak



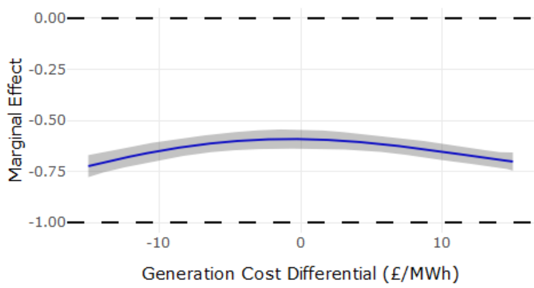
(b) partial effects of ΔW_t on ΔG_t, off-peak



(c) partial effects of ΔW_t on ΔC_t, peak



(d) partial effects of ΔW_t on ΔG_t, peak



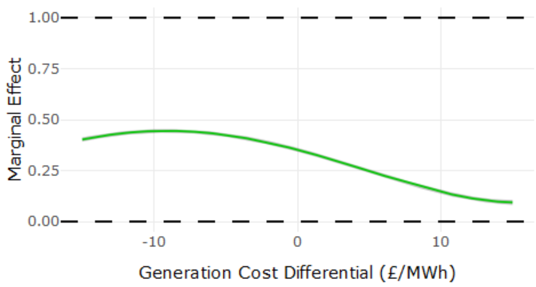
99% confidence intervals are plotted in Figure 2.6, with the x-axis representing the cost differential, PD_t, and y-axis representing marginal effects. Overall, the partial effects are negative, and $|\widehat{\partial \Delta C_t / \partial \Delta W_t} + \widehat{\partial \Delta G_t / \partial \Delta W_t}|$ is about 0.85, smaller than 1 (this is clearer in Table 2.5 below). Probing more deeply, if the regressions are run with 5 minute data the sum is lower, and if run aggregating the half-hourly data to daily data, the sum is close to 1.[20] The explanation is that in the very short run (5 minutes) CCGT and pumped storage (PS) respond, and gradually coal responds (if in merit) displacing PS, so that over the half hour coal had a higher share than over the 5 minutes. Similarly, over the course of the day, PS allows in-merit coal to play a larger role and so raising the total emissions displaced by that day's extra wind.

Figures 2.6a and 2.6b show off-peak relationships. The slopes of the curves reflect the impact of PD_t on switching the merit order: the steeper the slope, the stronger the impact. The shapes follow our earlier expectations — upward (downward) sloping with the steepest

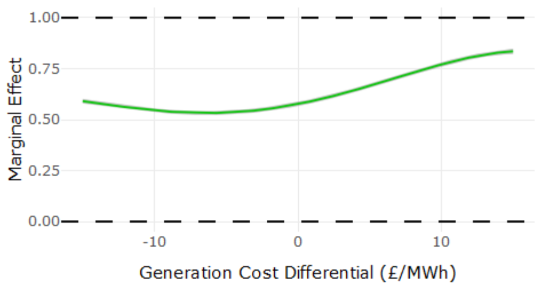
[20] See Appendix Table A.4 for the regression results using daily data.

Fig. 2.7 The estimated partial effects of ΔD_t on ΔC_t and ΔG_t, regressions (iii) and (iv)

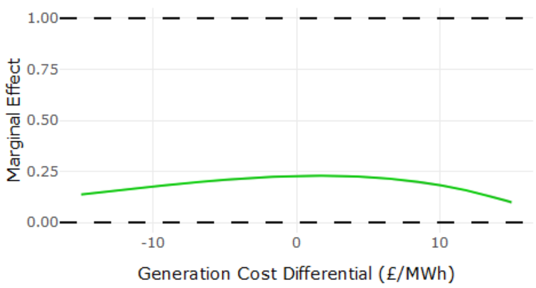
(a) partial effects of ΔD_t on ΔC_t, off-peak



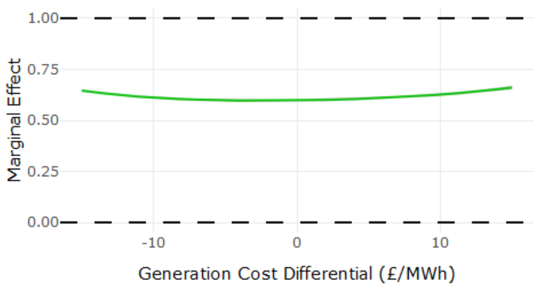
(b) partial effects of ΔD_t on ΔG_t, off-peak



(c) partial effects of ΔD_t on ΔC_t, peak



(d) partial effects of ΔD_t on ΔG_t, peak



slopes near $PD_t = 0$, and with descending slopes as PD_t moves away from zero, meaning that PD_t has little impact on the marginal fuel displaced by wind when the cost difference becomes large.

Thus in 2013 when $PD_t^{2013} = -£13.5$, a 1 MW change in wind supply *in off-peak periods* on average leads to a -0.56 MW change in coal generation and a -0.40 MW change in gas generation. In 2017 when $PD_t^{2017} = £13.5$, a 1 MW change in wind supply would on average result in a -0.06 MW change in coal generation and a -0.83 MW change in gas generation.

Figures 2.6c and 2.6d plot the peak relationships. The curvatures for the partial effects are more moderate than those in Figures 2.6a and 2.6b. This suggests that gas is always more responsive to wind variations during peak periods due to its flexibility. At the margin, 1 MW of wind displaces 0.09-0.22 MW of coal and 0.59-0.72 MW of gas.

Figures 2.7 shows the partial effects of ΔD_t on ΔC_t and ΔG_t (i.e., $\widehat{\partial \Delta C_t / \partial \Delta D_t}$ and $\widehat{\partial \Delta G_t / \partial \Delta D_t}$).[21] Again, Figures 2.7a and 2.7b plot the off-peak partial effects, and 2.7c and

[21] The 99% confidence bands are too narrow to be observable.

2.7d plot the peak partial effects. All partial effects are always positive, and $\widehat{\partial\Delta C_t/\partial\Delta D_t} + \widehat{\partial\Delta G_t/\partial\Delta D_t}$ is very close to $|\widehat{\partial\Delta C_t/\partial\Delta W_t} + \widehat{\partial\Delta G_t/\partial\Delta W_t}|$ for any given PD_t within the interval of study. Again, the impact of demand variations is buffered by pumped storage, leading to different emissions impacts over different time scales from 5 minutes up to one day.

The curvatures for the off-peak partial effects meet our initial expectations — downward sloping for coal and upward sloping for gas. As the generation cost for coal becomes higher (i.e. PD_t increases), gas becomes more sensitive to demand changes during off-peak periods. Thus when $PD_t^{2013} = -£13.5$, for a 1 MW change in the energy demand, coal on average contributes 0.42 MW and gas on average 0.58 MW. When $PD_t^{2017} = £13.5$, a 1 MW increase in demand would on average increase coal generation by only 0.10 MW and gas generation by 0.82 MW.

As with wind, in peak periods the marginal effects of demand do not vary much with PD_t. At the margin, 10%-23% of demand change is met by coal and 59%-66% by gas.

Besides the different signs, the impact of wind is similar to the impact of demand. In off-peak, the base load fuel is at the margin and responds to wind/demand changes. In peak hours, flexible CCGTs always provide the response. Any further differences between the partial effects of wind and demand are explained by the difference in predictability of wind and demand. As demand is more predictable, less flexible coal plant can be suitably scheduled ahead of time. Table 2.5 compares the two responses.

2.6.3 Short-run marginal displacement factor of wind

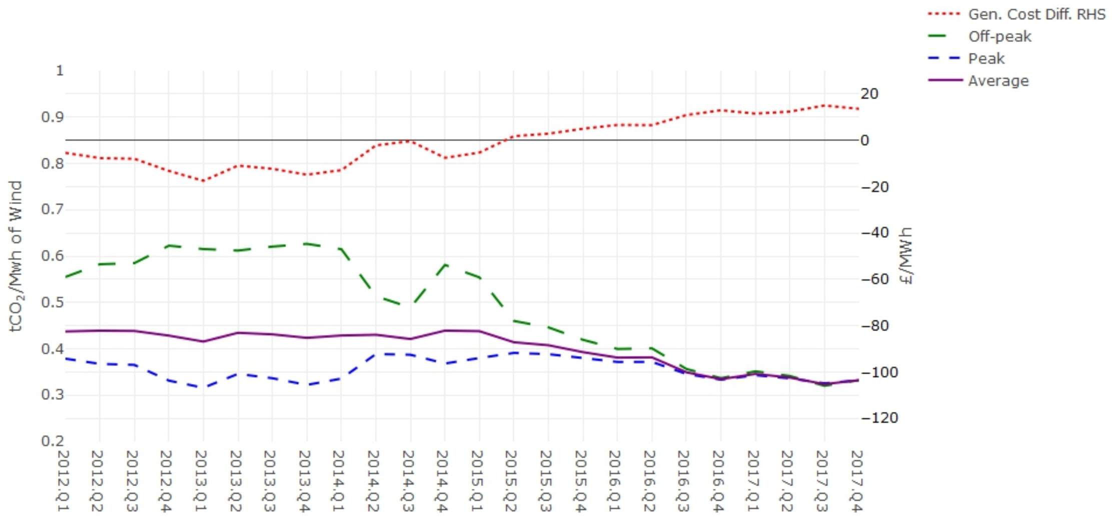
The estimation results from Figure 2.6 allow us to calculate the marginal CO_2 displacement of wind since 2012. For each half hour, given the generation cost differential, we first calculate the partial effects of ΔW_t on ΔC_t and ΔG_t. Then, we multiply the estimated partial effects by the emission coefficients of coal and efficient CCGTs respectively to obtain the SR-MDF.[22] The calculation is done separately for peak and off-peak and then combined to deliver the final result. Figure 2.8 plots the quarterly average SR-MDF of wind,[23] where the dotted curve represents the marginal cost differential between coal and gas (PD_t), which is to be read from the right-hand y-axis.

Figure 2.8 shows that the SR-MDF of wind in off-peak periods is decreasing during the period, with no strong trend for peak periods. The reason is straight-forward from Figure 2.6. When coal is cheaper and on base loading (before Q2 2015), coal responds more to wind

[22] We use the emission factor of 0.871 tCO_2/MWh for coal-fired power plants, and a weighted average of 0.337 tCO_2/MWh for efficient CCGTs.

[23] The corresponding Marginal Emission Factors (MEFs) are listed in Appendix Table A.5.

Fig. 2.8 The short-run marginal displacement factors of wind

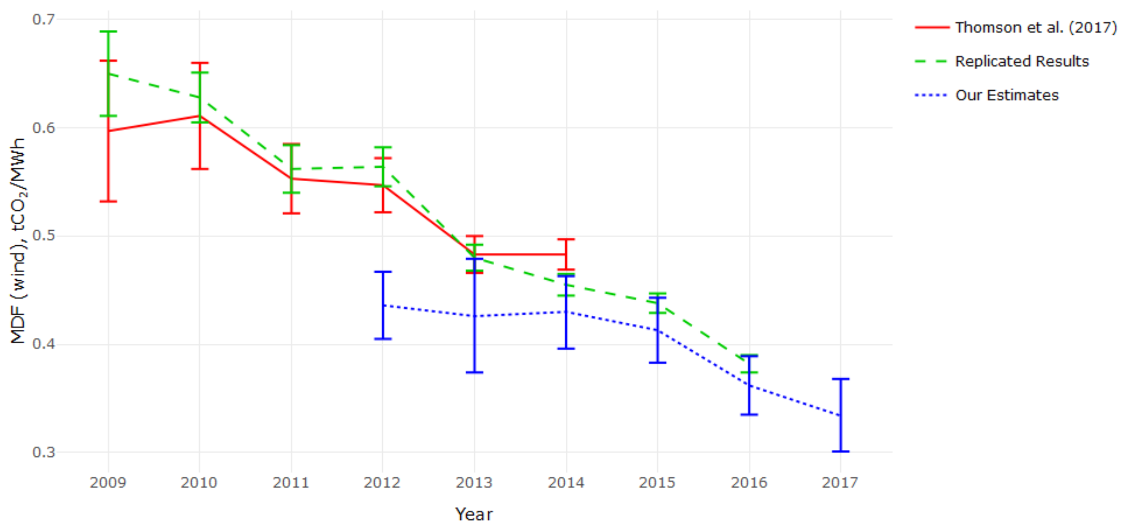


changes during off-peak periods. Since coal has a higher emission intensity than gas, the marginal CO_2 displacement of wind is higher when coal is the marginal fuel during these off-peak hours before Q2 2015. In peak hours demand is more variable, prices are higher, so CCGTs are in-merit and better able in respond quickly to variations in wind, so the cost differential has little impact on the peak SR-MDF of wind. The solid curve is the average SR-MDF after combining peak and off-peak periods, which is also in general negatively correlated with the generation cost differential (PD_t). The negative relationship is mainly driven by the dynamics of the SR-MDF during off-peak periods. In addition, the gradual phase-out of coal-fired power plants over this period also plays a non-trivial role on the decline of the SR-MDF.

The CPS almost doubled after Q2 2015, causing efficient CCGTs to provide base-load power, displacing coal. Since then, wind primarily displaces gas in both peak and off-peak periods causing the SR-MDF for off-peak periods to fall. Thus from Q1 2012 to Q2 2015, a 1 MWh short-run increase in wind supply would on average reduce CO_2 emissions by 0.43 tonnes; while from Q2 2015 to Q4 2017, it would on average only reduce CO_2 emissions by 0.36 tonnes.

The period 2012-2017 slightly overlaps with that studied (2009-2014) by Thomson et al. [147]. Figure 2.9 shows a comparison of the results. We also used the best readily available data to replicate Thomson et al.'s results and extend their estimates to 2016 (the detailed numbers are shown in Appendix Table A.6 together with details for the replication).[24]

Fig. 2.9 Comparisons on the patterns of annual MDFs, tCO_2(eq)/MWh



Despite using a rather cruder (but more accessible) data set, the replicated results on the SR-MDF are very close to those from Thomson et al. [147], especially for the years between 2010-2013. On the other hand, our estimates from non-linear regressions are overall smaller than those from Thomson et al. [147] and the replicated results, because we are using completely different emission factors[25] as well as different estimation methods. Despite that, the pattern for the dynamics of our estimated SR-MDF overlaps with the replicated results except for 2012, perhaps because we treat imports as overseas CO_2 emission and exclude their contribution.[26] Our results can be more intuitively explained by the merit-order effect given the fuel cost movements shown in Figure 2.3. Although the CPS was introduced on 1 April 2013, efficient CCGTs did not become base load until Q2 2015. Without a switch in the merit order there is no reason for any drastic change in the SR-MDF in 2013.

[24]We use the five-minute average generation by fuel type data from the Elexon portal which is only available up to Q1 2017.

[25]Thomson et al. [147] use well-to-tank net calorific values (NCV) and as a result, the average emission factors for coal (with 35.6% efficiency) and efficient gas (with an average of 54.5% efficiency) are, respectively 1.12 tCO_2eq/MWh and 0.416 tCO_2eq/MWh, much higher than the carbon emission coefficients found by other studies. See UK Parliament.

[26]It would be possible, but challenging, to determine the marginal plant and hence emissions from the transmission-constrained Continental electricity market.

Table 2.4 Marginal generation costs by fuels

	Marginal Cost £/MWh$_e$			
	no CO_2	zero CPS	base CPS	high CPS
Coal	£18.46	£23.68	£39.36	£50.68
CCGT new	£28.80	£30.80	£36.79	£41.12
CCGT older	£30.52	£32.63	£38.97	£43.54
CCGT oldest	£44.08	£47.15	£56.35	£62.99
Carbon Cost £/tCO_2		£6.00	£24.00	£37.00

To compare the SR-MDF with the LR-MDF to be discussed in the next section, we estimate the SR-MDFs under three difference carbon price scenarios — no CPS (full carbon price £6/tCO_2), base CPS (full carbon price £24/tCO_2), and high CPS (full carbon price £37/tCO_2). We choose these three particular carbon prices because the average EUA price for 2015 is around £6/tCO_2,[27] then the zero and base CPS cases simulate the 2015 fuel mix with and without the CPS. £37/tCO_2 corresponds to the high 2018 EUA price induced by the *Market Stability Reserve*. Table 2.4 gives the electricity generation cost by fuels under the three proposed scenarios, based on the fuel price and plant efficiencies given in Table 2.1.

Table 2.5 SR-MDF for the three carbon price scenarios

	Carbon Costs		
	£6/tCO_2	£24/tCO_2	£37/tCO_2
	Cost Differentials		
	£-6.98/MWh	£2.70/MWh	£9.70/MWh
$-\partial\Delta C/\partial\Delta W$	0.29	0.24	0.15
$-\partial\Delta G/\partial\Delta W$	0.56	0.60	0.69
SR-MDF	0.44	0.41	0.36
$\partial\Delta C/\partial\Delta D$	0.28	0.26	0.18
$\partial\Delta G/\partial\Delta D$	0.58	0.60	0.67
MEF	0.44	0.43	0.38

Notes: $-\partial\Delta C/\partial\Delta W$ is the coal Displacement Factor (DF, the decrease in Coal output for 1 MWh of Wind), $-\partial\Delta G/\partial\Delta W$ is the gas DF and SR-MDF = $-\partial\Delta CO_2/\partial\Delta W$ is the displacement of CO_2 in tCO_2/MWh of extra wind.

The SR-MDF and MEF under the three carbon price scenarios are given in Table 2.5, where the partial effects are averaged over peak and off-peak periods. As the carbon price increases, both $-\partial\Delta C/\partial\Delta W$ and $\partial\Delta C/\partial\Delta D$ decline, and both $-\partial\Delta G/\partial\Delta W$ and $\partial\Delta G/\partial\Delta D$ increase. This is driven by the merit-order switch during off-peak periods. The CPS forces gas (instead of coal) to respond to wind (and demand) changes during off-peak periods.

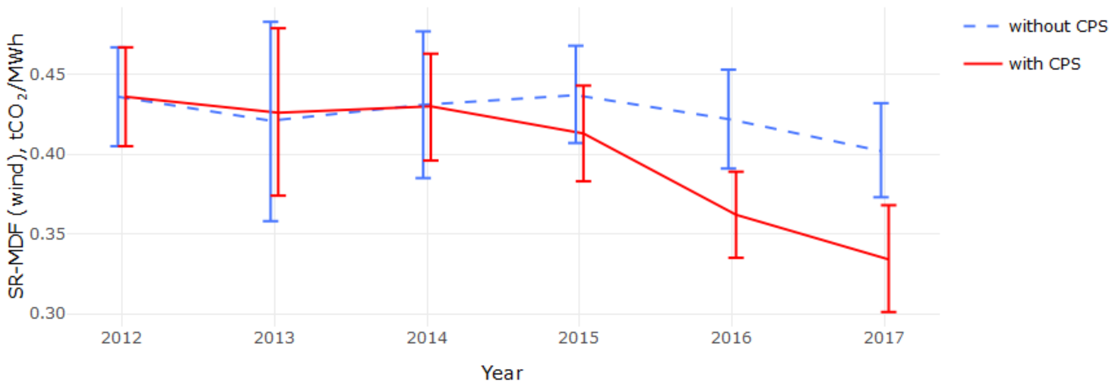
[27] The exact 2015 average was £5.85/tCO_2.

During peak periods flexible gas always provides the main response to wind (and demand) changes. As coal has a much higher emission factor, both SR-MDF and MEF decline with carbon prices.

2.6.4 The SR-MDF without the CPS

By treating fuel prices as exogenous, we can calculate the marginal effects of ΔW_t on ΔC_t and ΔG_t without the CPS by adjusting the generation cost differential (PD_t) in the regressions (iii) and (iv). We then multiply the marginal effects by the corresponding emission factors to derive the SR-MDF without the CPS. The patterns are shown in Figure 2.10.

Fig. 2.10 SR-MDF with and without the CPS



Without the CPS, the SR-MDF would stay relatively high, so the average SR-MDF in 2015 would be 0.44 tCO_2/MWh instead of 0.41 tCO_2/MWh, or 7% higher, while in 2017 it would be 0.40 tCO_2/MWh instead of 0.33 tCO_2/MWh, or 21% higher. The explanation is that without the CPS, both coal and gas costs would be lower, but the generation cost from coal would be much lower. Coal would continue on base loading, being the marginal off-peak fuel until late 2017, when the gas and EUA prices increase and coal becomes mid-merit even without the CPS. This explains why the SR-MDF stays high until late 2017. During this period, without the CPS, marginal wind displaces more CO_2, although the CPS shifts supply from coal to gas, reducing overall emissions.

2.7 Modelling the Long-run Carbon Savings from Wind

The long-run carbon savings from additional wind capacity is studied using a simulation model to determine dispatch with and without a significant increase in wind capacity. Deane et al. [49] do this for EU scenarios in 2030 and 2050, using Plexos to minimize total costs over a year. They assume inelastic time varying demand, and take account of pumped storage and "operational and technical constraints" (presumably transmission capacities, ramping, minimum load and other plant characteristics). Ofgem [115] uses the LCP EnVision model to simulate not just dispatch but also investment and retirements from 2010-2017 to simulate counterfactuals with and without some or all of the policy interventions, including the CPS. Ofgem is interested in the increase in wholesale electricity costs and the policy costs, but ignores any longer-run benefits (learning spill-overs inducing climate change mitigation elsewhere, as in Newbery [103]).

We use our simple hourly unit commitment model of the 2015 GB power system (Chyong et al. [37]) to examine the impacts of varying wind capacity on fuel mix and hence CO_2 emissions, for three carbon prices and two levels of wind capacity. In contrast to Ofgem [115], we do not model plant entry and exit, although the plant we simulate in 2015 is the plant listed as then present and consistent with our central carbon price (Ofgem [115], Figure A3, p.9). Thus we can examine the impact of additional wind capacity on future carbon savings. All cases take the plant available in 2015, but hold demand and all outputs (including interconnector flows) other than coal, gas, and pumped storage at their 2015 values.[28] The reference case takes the actual wind output in each hour of 2015 (an average wind year), and holds fuel and carbon prices constant across the year, so that variations in fuel prices and trade do not confound the variations of interest. The assumed fuel and the three carbon costs (EUA price plus CPS) are shown in Table 2.1, with the installed capacities, efficiencies and carbon intensities of key generation units.

The simulation determines an optimal hourly dispatch with predictable future demand and outputs of wind over the period of optimization. The simulations are re-run with 25% more wind in each hour (i.e. with 25%[29] more installed capacity at each location) to see how much coal and gas output is displaced in each hour and the resulting carbon savings, which in turn depend on the carbon price. Pumped storage (PS) is endogenous but only in arbitrage mode. Its more valuable use in short-term balancing cannot be handled in this deterministic model. The hourly resolution inevitably conceals short-run variations and represents the

[28]From Elexon Portal.

[29]The 2015 average wind generation is 3.7 GW. The 25% increase raises average wind generation to 4.6 GW, compared to the 2017 average wind generation of 5.1 GW. The increase is small in magnitude, and therefore is treated as a marginal increase. We also ran a 5% and 10% increase of wind, confirming that the LR-MDF is consistent with varying wind changes.

predictable component of plant commitment. We compare and contrast the long-run and short-run analyses in Table 2.6 and in Section 2.8.

Efficient unit commitment models fall short of describing market outcomes, as plant owners will typically set prices as a mark-up on their variable costs, by different amounts depending on their competitive position and their need to remain on the system. Interconnector flows and pumped storage will depend on market prices, not the system marginal cost. Modelling market prices at an hourly resolution is an enterprise with to date limited success, hence the need to interpret simulation results with care. Our deterministic modelling reduces the need for more flexible plant, probably increasing the role of coal in adjusting to changes, and understating total system costs.

Table 2.6 shows that the fuel price differences in the 2015 CPS case are small (£2.7/MWh) compared to differences in variable O&M costs, so that the effective operating costs of coal and gas are almost identical. That makes the optimal dispatch very sensitive to minimum down times and minimum stable generation. Small changes in these parameters lead to surprisingly large changes in $\Delta C/\Delta W$, and so should be treated with a degree of caution. When fuel price differences are sufficiently large the results are more robust to changes in the technical parameters. GB coal stations expect a very limited remaining life since the CPF was introduced, and have therefore likely reduced maintenance and moved outside the operating ranges that would be desirable for long and trouble-free operation, so taking industry standards for these parameters may not describe recent operating conditions. One of the advantages of our simple unit commitment model is that it can throw light on such sensitivities and thus indicate their robustness or its lack.

Table 2.6 gives the summary results that can be directly compared with the short-run results in Table 2.5. The first column shows that without the CPS and just the EUA of £6/tCO_2, the change (Δ) in wind output over the year of 8.11 TWh leads to a fall in CO_2 of 4.17 million tonnes, so the LR-MDF (shown as $-\Delta CO_2/\Delta W$) is 0.51 tCO_2/MWh. The SR-MDF is shown immediately below and is lower as the less predictable short-run response relies more on gas, while the long-run predictable change in wind allows more coal to be scheduled to adjust.

With the CPS at its actual value of £18/tCO_2, the CO_2 price is £24/tCO_2, and the LR-MDF is 0.60 tCO_2/MWh, again higher than the SR-MDF and for similar reasons. The fact that the LR-MDF increases with the CPS while the SR-MDF falls is discussed in more detail below, but primarily reflects the very close variable costs of coal and gas (when variable O&M costs are included, making the MDF very sensitive to technical parameters such as ramp rates and minimum stable generation. A small increase in the minimum stable generation of coal considerable lowers the LR-MDF.

As with the SR-MDF, there is a slight fall in the LR-MDF moving to a CO_2 price of £37/tCO_2. Summarising, the LR-MDF of wind rises from 0.51 (tCO_2/MWh) at zero CPS, to 0.60 with a CPS of £18/tCO_2, then it slightly falls to 0.57 at the highest carbon price as coal is squeezed out of the system.

Table 2.6 Displacement factors for the three carbon price scenarios, 2015 generation mix

	Carbon Costs					
	£6/tCO_2		£24/tCO_2		£37/tCO_2	
	Cost Differentials					
	£-6.98/MWh		£2.7/MWh		£9.7/MWh	
	TWh	ΔCO_2	TWh	ΔCO_2	TWh	ΔCO_2
ΔC	-2.77	-2.41	-3.95	-3.44	-3.55	-3.09
ΔG	-5.26	-1.76	-4.07	-1.39	-4.50	-1.54
ΔW	8.11	-4.17	8.11	-4.83	8.11	-4.64
$-\Delta C/\Delta W$	0.34		0.49		0.44	
$-\Delta G/\Delta W$	0.65		0.50		0.56	
LR-MDF	0.51		0.60		0.57	
(SR-MDF)	(0.44)		(0.41)		(0.36)	
$\Delta C/\Delta P_c$ TWh/£			-4.62		-0.24	
$\Delta G/\Delta P_c$ TWh/£			4.62		0.25	
$\Delta CO_2/\Delta P_c$ Mt/£				-2.47		-0.12

Notes: $-\Delta C/\Delta W$ is the coal Displacement Factor (DF, the decrease in Coal output for 1 MWh of Wind), $-\Delta G/\Delta W$ is the gas DF and SR-MDF = $-\Delta CO_2/\Delta W$ is the displacement of CO_2 in tCO_2/MWh of extra wind. $\Delta X/\Delta P_c$ is the change in output of X (coal, gas or CO_2) for a £1 increase in the CO_2 price going from £6-24/tCO_2 or from £24-37/tCO_2, measured at the base level of wind.

Note that in Table 2.6, coal and gas changes ($-\Delta C/\Delta W - \Delta G/\Delta W$) add up to about unity following a 1 MWh of wind change, while in Table 2.5, the sum of changes is about 0.85 MWh, with the rest mainly coming from pumped storage and imports. If the half-hourly data are aggregated to daily data, the econometric estimate of this sum is also about unity, suggesting that the difference is largely explained by pumped storage that averages to nearly zero over the day. The long-run model aggregates over a year, which has the same effect as daily averaging. Furthermore, the unit commitment model makes the assumption that only coal, gas, and pumped storage respond to wind changes, as imports are held at their actual 2015 levels. If the price impact of more wind had been considered, prices would have been lower, reducing net imports slightly, so increasing fossil generation and slightly raising the LR-MDF. Against that, higher wind capacity would likely lead to coal exit, countering this effect.

The last three lines of Table 2.6 give the estimated average impact of raising the carbon price P_c by £1/tCO_2 on the output of coal, gas and CO_2.[30] The CPS switches the merit order, so that on average a £1/tCO_2 increase in the CPS (over the range zero CPS to £18/tCO_2) significantly lowers coal generation by 4.62 TWh/year, displaced by gas. Since gas plants emit less CO_2, the CPS saves 2.47 million tCO_2/£/year. Increasing the total CO_2 price further to £37/tCO_2 has a more moderate impact on the fuel mix and emissions — a £1/tCO_2 increase in the CO_2 price results in 0.24 TWh decline in coal generation (displaced by gas) and 0.12 million tCO_2 reduction. This is because increasing the carbon cost from £24/tCO_2 to £37/tCO_2 does not change the merit order.

We also calculate the capacity factor (CF)[31] as well as the coefficient of variation (CV) for the reference wind cases, summarised in Table 2.7. In the zero CPS case coal has a CF of 83% and a coefficient of variation (CV) of output of 25%, while gas has a CF of 22% (CV 91%), consistent with coal on base load and gas providing mid-merit variable output. As gas is displaced by the extra wind, its carbon benefit is low.

Table 2.7 Capacity factors (CF) and coefficients of variation (CV), 2015 base wind

	Carbon Costs					
	£6/tCO_2		£24/tCO_2		£37/tCO_2	
	CF	CV	CF	CV	CF	CV
Coal	83%	25%	18%	118%	16%	129%
CCGT	22%	91%	70%	29%	72%	29%

The situation changes considerably with the CPS at £18/tCO_2. Coal output is lower and more variable (CF falls to 18% and CV rises to 118%), while gas CF rises to 70% (CV 29%), consistent with gas on base load with coal displaced by the extra wind, raising its carbon benefit. This case is very similar to the high carbon cost (£37/tCO_2) case, because of the same merit order.

PS is endogenous in the simulations and will be driven by peak and off-peak variable cost differences, which will vary between different wind capacity scenarios. However, it is important to remember that actual PS is partly driven by arbitrage, which is driven by wholesale price differences that likely differ from variable cost differences. The main revenue earner for pumped storage is providing balancing and ancillary services, which are

[30] Calculated by differencing the outputs at £6/tCO_2 and £24/tCO_2 and dividing by £18/tCO_2 (=24-6) to give the first set of values (in the £24/tCO_2 column) and similarly differencing the outputs at £37/tCO_2 and £24/tCO_2 to give the final column.

[31] This is given by the average output relative to the maximum observed output, which is below the nominal capacity. This seems a more relevant measure for CCGTs, where there is a large tail of less efficient plant that would otherwise give a very low CF for gas as a whole.

not modelled. To test for robustness, we re-run all simulations with half the effective PS capacity (the rest reserve for balancing), and reassuringly, the results are close.

As PS has a round trip efficiency of about 75%, if more storage is required, then losses will lead to more MWh of fossil generation, so the sum of the output changes of coal, gas and wind is slightly (1%) more than zero. However, variations in pumped storage do not lead to changes in emissions, as we assume that all pumped storage will be used over the course of the day either in arbitrage or balancing mode, regardless of the actual wind output.

As an additional test for the robustness of the wind scenarios, the model was re-run with 10% and 5% more wind capacity, and these confirm that the LR-MDFs are within 0.01 of those at 25% extra capacity.

2.7.1 The variation of LR-MDFs with Residual Demand

Figure 2.11 graphs a rolling average of the various displacement factors against residual demand.[32] The graph shows the displacement of coal output ($-\Delta C/\Delta W$), gas output ($-\Delta G/\Delta W$), pumped storage output ($-\Delta PS/\Delta W$), and the implied carbon saving, the LR-MDF ($-\Delta CO_2/\Delta W$, tCO_2/MWh) as a function of residual demand (taken as the sum of coal, gas and pumped storage) for the 2015 power system, the actual 2015 CPS, and reference wind case. It also shows the deviation of the average wind over these hours compared to the annual average. We expect a low residual demand (RD) to represent off-peak and high RD to represent peak hours.

When the total CO_2 price is £24/tCO_2, coal is mid-merit and gas is base load. When RD is low, wind displaces mostly gas as coal is running at minimum stable levels, but at higher RD when prices are high enough to make coal profitable, coal can respond flexibly ($-\Delta C/\Delta W$ rises to above unity) while gas is base load and hardly varying ($-\Delta G/\Delta W$ approaches zero). Coal (and CO_2) displacements move in counterpoint with gas, as $-\Delta C/\Delta W - \Delta G/\Delta W - \Delta PS/\Delta W = 1$, and averaged over many hours $\Delta PS/\Delta W$ is small, as the graph show. Thus the LR-MDF for wind is smaller at low levels of RD, and higher at high RD. As a result the LR-MDF is larger than for the zero CPS case discussed below.

Figure 2.12 repeats this for the case with no CPS (just the EUA £6/tCO_2). This time coal does not respond at all at high RD when it is at base load, but does respond more strongly than gas at low RD, so the LR-MDF is high at low RD (off-peak) and lower for higher RD (peak periods) leading to a lower average LR-MDF.

[32] The graphs are constructed by first ranking the simulated hourly generation by residual demand, averaging the MW of coal, gas, pumped storage and wind over 672 ranked non-consecutive hours, and then calculating the ratios of interest based on the averaged outputs. This smooths out unimportant fluctuations caused mainly by pumped storage which differs for the same hours but with different levels of wind capacity. Residual demand is averaged over the same number of hours (672).

Fig. 2.11 Displacement factors v.s. residual demand, £24/tCO_2

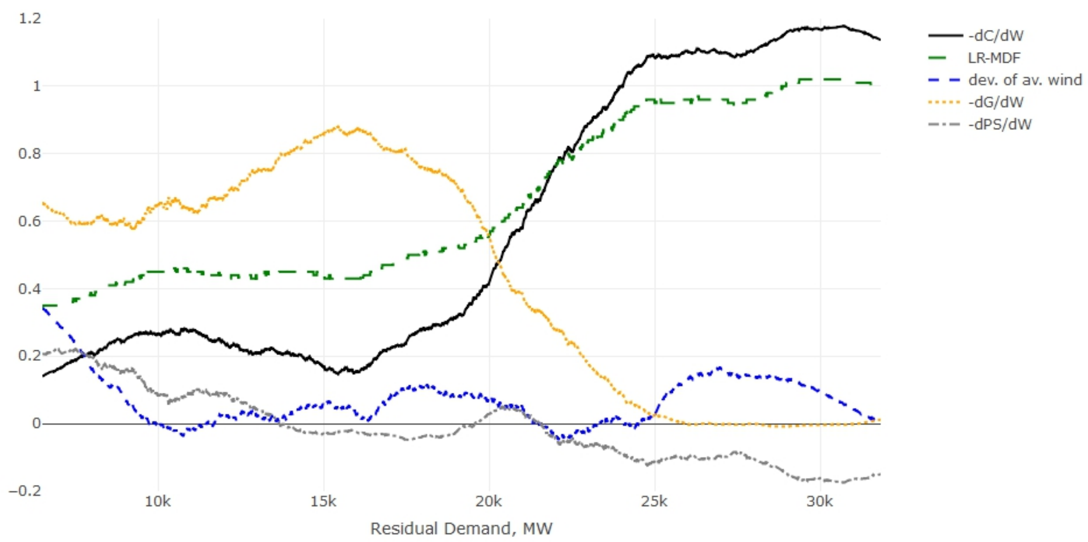
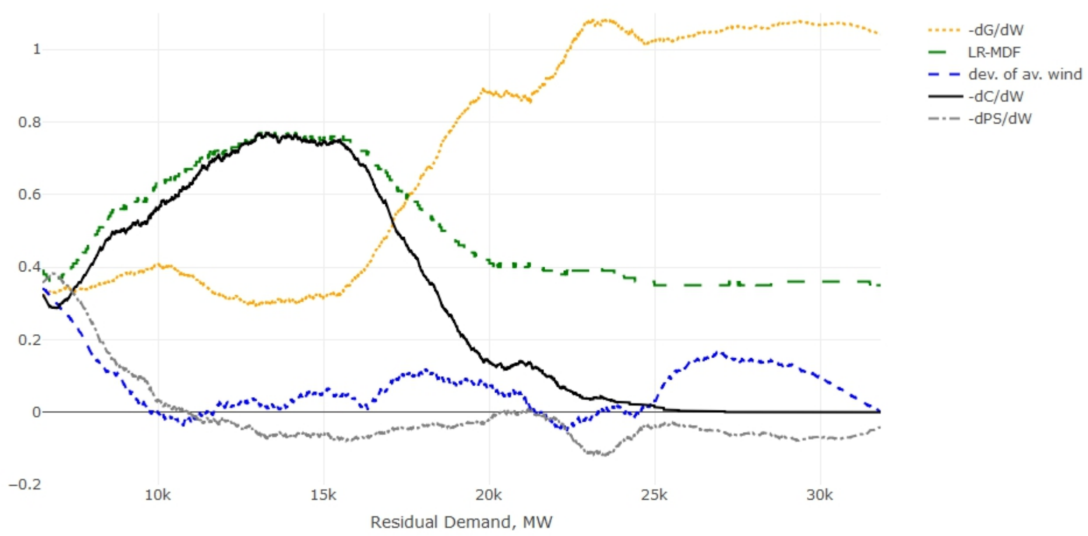


Fig. 2.12 Displacement factors v.s. residual demand, £6/tCO_2



Finally, at the very high carbon prices seen towards the end of 2018 (£37/tCO_2), the patterns are extremely similar to the actual 2015 CPS case in Figure 2.11, and are plotted in Appendix Figure A.1.

2.8 Comparing the long-run and short-run carbon savings

Our LR-MDF measures the impact of more wind capacity on the merit order under different carbon prices, but holding other plant and trade flows constant. More wind turbines lower the residual demand, edging out the most expensive fuel plants. When the variable cost for coal plant is higher than gas, a large increase in wind capacity would likely force the closure of some coal stations, until the wholesale price rises enough to make the remaining stations sufficiently profitable. As plant exit is not included, the LR model may over-estimate the maximum output that coal can supply. Coal exit would likely reduce the LR-MDF at higher carbon prices. When the coal is entirely phased-out, building more wind turbines is likely to displace the less efficient CCGTs (which are still less carbon-intensive than coal).

In the short-run (the period in which plants are committed to deliver in future hours) the carbon savings will be affected by the types of plant that respond to the volatile hour-to-hour wind changes (some are predictable day-ahead and intra-day while some are not). Which plant can increase or decrease output sufficiently rapidly will depend on its flexibility and the cost of ramping up and down, and this may not be the plant where the residual demand meets the static merit order. However, the full impact of changes in wind output in any short period continues to be felt later in the day, as initially the more flexible pumped storage takes the strain, but unwinds later in the day, allowing coal (if in merit) time to respond. Thus the half-hourly MDFs are likely to be lower than the daily MDFs (as we found econometrically). When coal plants are entirely phased out, CCGTs are likely to be the only fossil plant that responds to wind changes, while electricity storage and cross-border trading may play more important roles in avoiding excess wind curtailment and providing more reliable balancing and ancillary services.

Tables 2.5 and 2.6 give the SR and LR impacts of wind. The difference between LR- and SR-MDFs is mainly the difference between short-run responses to *volatility* (an equal chance of an increase and decrease in wind output over a short period of time, here half an hour) and *certainty* of an increase in wind from installing more wind capacity. Over the course of a day, short-run fluctuations in output are buffered by pumped storage (PS) and flexible CCGT, but later on if coal is in merit (on base-load), it can replenish the PS. It is arguable that it is the shorter run MDF that is relevant, as if wind changes did not precipitate changes in PS output, then the larger variations in demand would have depleted the PS, with the same fuel replenishing PS off-peak. With the predictable fluctuations in demand and wind considered in the unit-commitment model, PS plays only an arbitrage role and in-merit coal can be scheduled to respond to these predicted variations in residual demand, raising the MDF.

In the long-run, wind supply is driven by wind capacity, and building more wind turbines would certainly increase predictable wind output, phasing out the more expensive fossil plants. In the short-run, wind output solely depends on wind speed. Forecast errors and varying (residual) demand require more flexible plant rather than the cheaper scheduled plant to respond to the wind changes.

The LR-MDF rises (from 0.51 to 0.60 or by 18% for 2015 data) as the total carbon price rises from £6/tCO_2 to £24/tCO_2. This is because the CPS moves coal from base-load to mid-merit where raising wind capacity is expected to displace coal rather than gas. In the deterministic model, coal can be scheduled to vary in response to future predicted wind variations and so plays a larger role than in the short-run econometric estimates, leading to a higher (and in this case an increase in the) MDF.

The econometric analysis shows that flexible CCGTs always respond to wind changes during peak periods; while for off-peak periods, the cheaper fuel responds to wind changes (the more costly fuel is likely at minimum load). In 2015 the variable costs of coal and gas are fairly close, and the £18/tCO_2 of CPS made coal more expensive than gas, shifting the marginal fuel for off-peak periods from coal to gas. As a result, the SR-MDF without CPS is higher than the SR-MDF with the CPS. Precisely, the CPS in 2015 lowered the SR-MDF from 0.44 to 0.41 (all tCO_2/MWh) or by 7%.

The relevant policy issue is whether increasing wind capacity reduces emissions, and the answer will be primarily driven by the LR-MDF. However, it is also worth noticing that the actual operation of the electricity system in real time requires flexible responses coming from possibly different plants than the apparently marginal plants suggested by the static merit order. If the increase in wind penetration has on average raised wind generation by 1 GW, then the amount of CO_2 displaced by the 1 GW of wind will depend on the LR-MDF. If the increase in wind penetration makes wind more volatile and increases the (half-hourly) changes of wind supply by an average of 0.1 GW, then the SR-MDF will explain the impact of that 0.1 GW of wind changes on CO_2 emission. When CCGTs become the only type of fossil plants in the market following the phase-out of coal plants, the LR- and SR-MDF converge as only gas is left to respond to long-run and short-run changes in wind supply.

2.9 Conclusion

This chapter has investigated the effect of the Carbon Price Support (CPS) on the carbon saving from wind by examining the impact of wind on the more carbon-intensive coal and less carbon-intensive CCGT outputs. The evolution of the fuel mix from 2010-2017 strongly suggests that gas has displaced coal, and that wind has displaced both, but as the clean spark and dark spreads have varied substantially over this period with varying fuel and carbon prices, a more detailed examination was undertaken to tease out the various effects. The unit commitment simulation model explores the effect of different total carbon prices on the carbon savings from a significant increase (25%) in installed wind capacity, holding fuel prices constant. At 2015 gas and coal prices, the CPS at an additional £18/tCO_2 on an EUA price of £6/tCO_2 switches coal from base-load to mid-merit, so now coal rather than gas is displaced by extra wind capacity, *increasing* the carbon benefits of wind investment modestly. At higher total carbon prices, coal output decreases and moves more to peak hours, resulting in a smaller carbon savings from wind investment. This increase is, however, sensitive to technical parameters that are hard to identify in ageing coal plant, and could easily be reversed to a fall in the LR-MDF with the CPS.

The short-run impact of half-hourly varying wind on the fuel mix and emissions was explored econometrically. Variations in fuel and carbon prices as well as wind capacity and final demand over a longer time period (2012-2017) identify the drivers of the Marginal Displacement Factor (MDF) of wind quite precisely. The econometric study suggests that the SR-MDF depends on demand (i.e. which fuel type is running at the margin), the merit order, and the flexibility of fossil plants. Specifically, when demand is low (off-peak), base-load plant responds more strongly to short-run wind changes. However, when demand is high and so is its variability, more flexible CCGTs are better able to respond. Hence CCGTs are the marginal fuel during peak hours (07:00-23:00) regardless of the merit order, while coal would only be the marginal fuel during off-peak hours (23:00-07:00) when coal provides the base load. The CPS switches the merit order moving coal to mid-merit, but the more flexible CCGTs become the marginal fuel for the entire day, *lowering* the SR-MDF slightly.

We argue that following an increase in wind capacity, the LR-MDF explains the impact of increasing wind penetration on CO_2 emission, while the SR-MDF explains the impact of increasing wind volatility (i.e. half-hourly wind changes) on CO_2 emission.

Both the simulation and the econometrics confirm that the impact of wind depends quite sensitively on the state of the system — which plant are running and whether they are constrained by minimum loads, capacity, or ramping limits, which in turn depend on the time period over which wind varies. The fuel mix depends on fuel and carbon prices and the levels of residual demand. Different countries have very different plant mixes, and so the carbon benefits of additional renewables capacity will also vary, while over time, fuel and carbon prices as well as the plant mix will also vary. This chapter shows how the emissions benefits can be measured for a given plant mix and set of fuel and carbon prices, implying that country level detailed modelling will be needed to understand their impacts.

Chapter 3

The Cost of Trade Distortion: Britain's Carbon Price Support and Cross-border Electricity Trade

3.1 Introduction

For economists, the natural policy instrument to reduce CO_2 emissions is a price on carbon, preferably via a tax rather than a tradable permit, given the persistence of CO_2 and uncertainties about cost and damage functions (e.g. Nordhaus [109], Weitzman [152], Andersson [8]). It is not the only instrument, and there are strong arguments for performance and emission standards (as distributionally more acceptable, or more acceptable to lobby groups, and as a powerful incentive to develop more efficient and lower emitting technologies). Direct innovation support, or indirect demand-pull through renewables targets also play their part. The EU's *Renewable Energy Directive* (2009/28/EC) therefore created the first multi-nation Emissions Trading System (the EU ETS), put in place efficiency targets (and more detailed industry-specific standards for vehicles, housing, appliances, etc.) and set country-specific targets for renewable energy.

Although a carbon tax may create considerable carbon benefit to the world, its impact can be reduced for two reasons - some leakage of carbon through imports and some cost increases because of a failure to equate the full *social marginal cost* of the carbon-intensive traded goods (e.g. Babiker [10], Elliott et al. [55], Aichele and Felbermayr [4]). Regional schemes like the EU ETS partially mitigate this by agreeing a uniform carbon price for some industries (the covered sector responsible for about half the total EU's emissions). Initially the EU ETS delivered plausible carbon prices, rising to nearly €30/tonne CO_2, but with the end of the first trading period and no banking, prices fell to zero. The second period started well, but the 2008 financial crisis and increased renewables targets reduced demand for allowances (EUAs), causing prices to fall, reaching their lowest level in 2011.

The prolonged failure of the EU ETS to give adequate, credible and sufficiently durable carbon price signals caused increasing concern in almost all Member States, but no country was effective in forming a coalition to reform the ETS in the first few years after 2008, and, with the earlier exception of Nordic countries, no country was willing to impose additional carbon taxes, fearing carbon leakage. The United Kingdom (UK) was, however, leading the world in imposing legally-binding emissions targets through the *Climate Change Act 2008* and was facing an increasingly urgent need for new generation investment. In response to both pressures, as part of the evolving *Electricity Market Reform*, the UK Government announced plans for a Carbon Price Floor (CPF) to come into effect in April 2013, intended to make up for the failure of the EU ETS. The CPF was implemented by publishing a Great Britain (GB)[1] Carbon Price Support (CPS) added to the EUA price to increase it to the projected CPF. The CPS grew from £4.94/tCO_2 in 2013 to £9.55/tCO_2 in 2014, and has been stabilised since 2015 at £18/tCO_2.

Consequently, the total GB carbon cost rose from £5/tCO_2 in early 2013 to nearly £40/tCO_2 by the end of 2018. Figure 3.1 shows the evolution of the (nominal) GB and the EU carbon prices. The two curves start diverging in 2013, with the gap becoming wider in 2014 and 2015. The dashed line represents the GB carbon cost target when the CPF was announced. It was not until late 2018 that the GB carbon cost finally met the initial trajectory, thanks to the reform of the EU ETS, which introduced a *Market Stability Reserve* that removes excess EUAs and increases its price (Newbery et al. [104]).

While the EU ETS should harmonise carbon prices and thus reduce distortions within the EU, it is still prone to leakage to the rest of the world. The main industries affected by carbon leakage are carbon-intensive traded goods such as steel, aluminium and cement. Fowlie et al. [67] choose US cement for a case study as it has experienced up to 20% import penetration, and is also highly concentrated. The electricity sector is, however, considerably more carbon intensive. In the EU-28, electricity accounts for just over 20% of total greenhouse gas (GHG) emissions, with very little decrease since 1990, while Figure 3.2 shows considerable fluctuations for the UK, remaining higher than the EU until the recent sharp decrease as coal has been driven out of the system by increases in carbon prices.

The electricity sector is therefore of central importance when studying the impact of differential carbon prices. It has the added advantage that electricity is not widely traded

[1] Northern Ireland, which is part of the Single Electricity Market of the island of Ireland, is exempt to preserve an equal carbon price on the island.

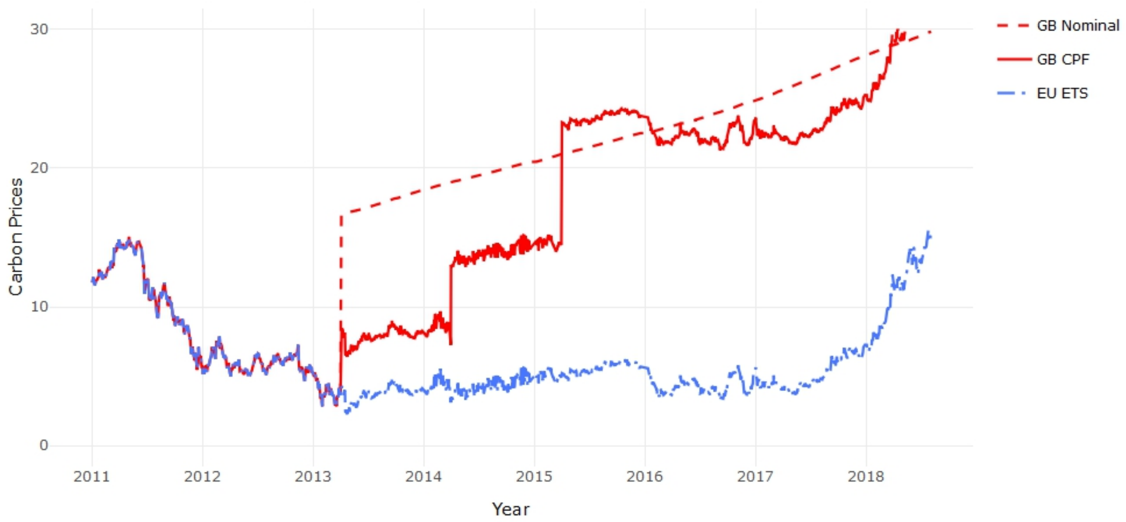


Fig. 3.1 The European and GB carbon prices in power sectors, £/tCO_2

Source: investing.com

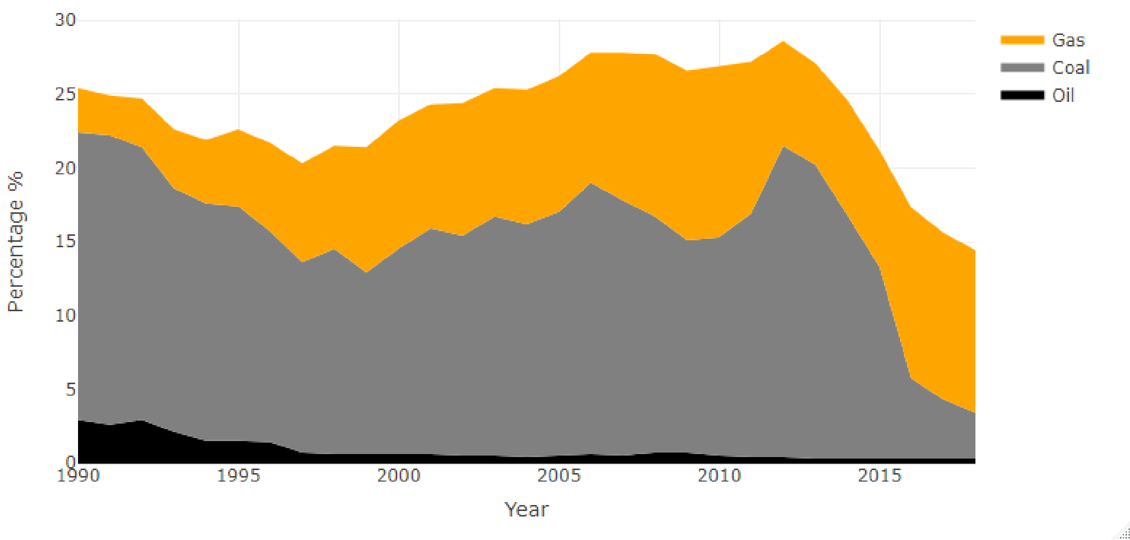


Fig. 3.2 UK CO_2 emissions from electricity sectors as a share of total emissions, 1990-2018

Source: Department for Business, Energy and Industrial Strategy (BEIS): Provisional UK greenhouse gas emissions national statistics.

outside the boundary of the EU, but within the EU, Great Britain (GB) faces potentially a 13% import share (and an actual share of 6.4% in 2018). A study of differential carbon prices within EU's Integrated Electricity Market[2] therefore isolates the impact, and allows us to ignore the rest of the world, except for the impact on global emissions.[3]

This chapter develops a methodology for quantifying the impact of an asymmetric carbon tax on electricity trade within a closed region such as the EU or North America. While it is relatively simple to characterise the qualitative impact – an increase in domestic and foreign wholesale electricity prices, an increase in imports, etc., any serious policy analysis also needs to quantify these impacts, to judge whether they are sufficiently large to justify policy action, and that is the purpose of this chapter.

The EU's *Third Electricity Directive 2009/72/EC* came into force in 2014, requiring market coupling of interconnectors. Before market coupling, traders had to buy interconnector volume and direction before knowing the market clearing price at each end, often resulting in inefficient trades. Market coupling ensured that interconnector capacity would be cleared at the same time as electricity markets, securing efficient trade. If market prices can be equilibrated without violating interconnector capacity constraints, prices at each end will be the same. Otherwise, trade will be set at full capacity and prices will diverge.

GB, The Netherlands and France have all been coupled since early 2014, while the interconnector between GB and the Single Electricity Market of the island of Ireland (comprising Northern Ireland, part of the UK, and the Republic of Ireland) was only coupled in October 2018. The interconnector linking GB to Belgium was not commissioned until 2019. We therefore restrict our study to GB's trade with France and The Netherlands from early 2014 to late 2018, before these other linkages became coupled.

This chapter quantifies the costs and benefits of cross-border electricity trading between interconnected countries in the presence of asymmetric distortionary carbon taxes. It takes GB as a case study and quantifies the impact of the CPS on electricity prices, interconnector flows, congestion income (from buying low and selling high), and social value from trade. It also estimates the deadweight loss and carbon leakage in the electricity sector created by the asymmetric carbon taxes. This has implications for the design and ideally harmonisation of the EU carbon tax to improve the efficiency of electricity trade.

We estimate that over 2015-2018 when the CPS stabilised at £18 (€20) /tCO_2, the CPS raised the GB day-ahead price by an average of €11.43/MWh (about 28% of the GB wholesale price) after allowing for replacement by cheaper imports. The CPS increased GB imports by 12.4 TWh/yr (about 4% of the GB annual electricity demand), thereby reducing carbon tax revenue by €101 m/yr (about 10% of the 2017 CPS tax receipts). The commercial

[2]The EU's Integrated Electricity Market opens national wholesale and retail electricity markets to trade and competition across the EU.

[3]Electricity prices will feed through to other exporting industries and will give rise to some additional leakage, but this will be ignored in the present chapter.

value of interconnectors (measured by congestion income) increased by €153 m/yr (by 80% relative to the zero CPS case), half of which was transferred to foreign interconnector owners. The sum of the congestion income and the importer and exporter surplus is the social value of interconnector at €250 m/yr, but the asymmetric carbon taxes created deadweight losses of €80 m/yr, about 4% of the global emissions reduction benefit of the CPS of €2 bn/yr. Increased French exports raised French wholesale prices by 3.5% and Dutch wholesale prices by 2.8%. Finally, about 1.3% of the CO_2 emission reduction is undone by France (-0.4% by the Netherlands), and the monetary loss of this carbon leakage is about €27 m/yr (€-9 m/yr for The Netherlands), in total €18 m/yr.

3.1.1 Literature review

The Coase theorem (Coase [43]) states that with well-defined property rights and sufficiently low transaction costs, bargaining will give Pareto efficient outcome regardless of the initial allocation of the property rights. However, the Coase theorem does not apply in international environmental policy, because the assumptions of "sufficiently low transaction costs" and "well-defined property rights" are mostly violated in pollution and GHG emissions markets (Pethig [122]). Furthermore, the existence of non-participants in the bargaining process (e.g. the uncommitted countries in the Kyoto and Paris Protocols) potentially leads to free-riding (Barrett [13]), resulting in carbon leakages. In the long run, this may also relocate capital and international firms (e.g. Markusen [96], Hoel [81], Rauscher et al. [127], Elliott et al. [55]). A second-best solution is to set tariffs or boarder taxes. Böhringer et al. [16] show that the use of carbon tariffs is a credible and effective threat in terms of inducing uncommitted countries to adopt emission controls.

In early 2000s, literature had mostly focused on the impact of unilateral carbon taxes on the macro-level bilateral trade and carbon leakage under the 1997 Kyoto Protocol. Elliott et al. [55] use a computable general equilibrium model to predict that countries uncommitted to the protocol will undo 20% of the reduction made by the committed countries, and adding full border tax adjustments would eliminate the leakage. Babiker [10] uses a similar model to predict that the leakage rate can be as high as 130%, resulting in higher global emissions. Aichele and Felbermayr [4] conduct an empirical *ex-post* evaluation of the protocol and find that the committed countries have increased 8% of its carbon imports, and the emission intensity of their imports has increased by 3%. Harstad [75] argues that the solution to the market distortion is to allow countries to trade their emission allowance, while Shapiro [138] suggests proposing regional carbon taxes from shipping to increase global welfare.

Fowlie et al. [67] look at the domestic distortions arising from the oligopolistic nature of the cement market, where at high carbon taxes domestic market power is increased. Leakage makes matters worse, and both effects can be counteracted by suitable policies, including a Border Tax Adjustments (BTA). Metcalf [98], in designing a politically acceptable carbon tax for the US, proposes a BTA to offset trade distortions, and an earned income tax credit designed to be distributionally neutral. Bovenberg and Goulder [20] look at environmental tax distortions in a closed economy, finding that a full corrective environmental tax (that fully internalises the externality) would create additional distortions if there are other distorting revenue-raising taxes, arguing for a lower than Pigouvian tax on such externalities. As the GB carbon tax does not carry any BTA it can be expected to have distortionary impacts on trade, while its interactions with the rest of the tax system will be ignored here (as the total demand for electricity is assumed inelastic in the short run).

Studies of carbon taxes and electricity markets have so far focused on their price impacts (e.g. Fabra and Reguant [56], Sijm et al. [140], Fell [61], Kirat and Ahamada [91], Jouvet and Solier [86], Wild et al. [155]), on the fuel mix and greenhouse gas emissions (e.g. Di Cosmo and Hyland [51], Cullen and Mansur [46], Staffell [142]), and on investment decisions within the power sector (e.g. Green [72], Fan et al. [57], Richstein et al. [129]). Fowlie [66] is perhaps the most useful for this chapter in that the author uses a numerical model to simulate CO_2 emissions from California's electricity industry. Fowlie [66] suggests that it is much more expensive to reduce CO_2 emission under a carbon tax that excepts out-of-state producers than a carbon tax levies on all producers.

To the best of our knowledge, there is no *ex-post* econometric estimation of the effect of a carbon tax on cross-border electricity trade, nor of the deadweight loss involved when applying carbon taxes asymmetrically across two electricity markets.

3.2 The British Carbon Price Floor and Carbon Price Support

The British-only Carbon Price Floor (CPF) distorted cross-border electricity trade, while market coupling ensures that the high-price country always imports and the interconnector capacity is efficiently used, simplifying the analysis. All EU Member States, together with GB until the end of 2020,[4] are members of the EU ETS designed to deliver a common carbon price. The CPF was implemented by the Carbon Price Support (CPS) (a carbon tax on generation fuels) which, with the EUA price was intended to increase the price up to the projected CPF. The CPS grew from £4.94/tCO_2 in 2013 to £9.55/tCO_2 in 2014, and has been stabilised since 2015 at £18/tCO_2.

[4]See GOV.UK.

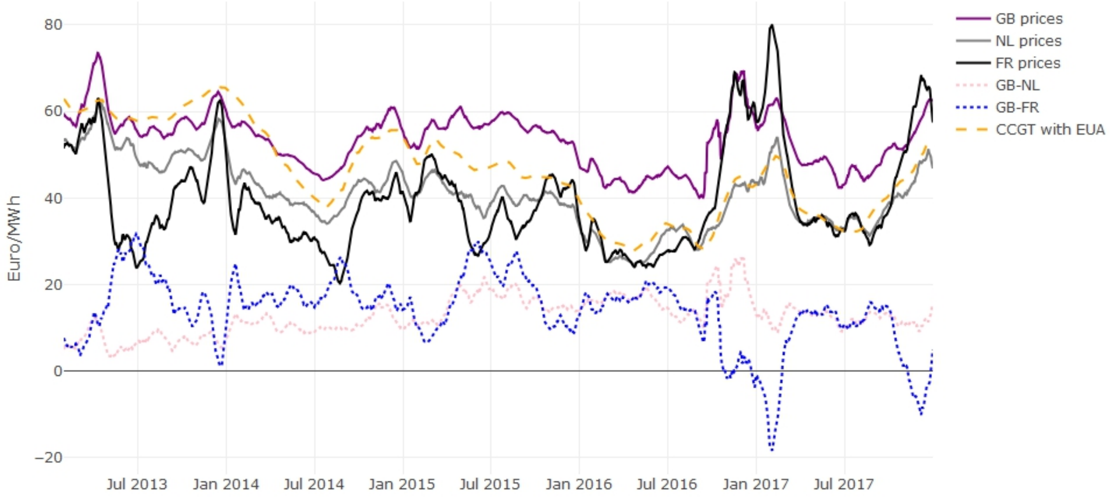


Fig. 3.3 28-day lagged moving average day-ahead prices, 2013-2017

Source: Epex Spot and Nord Pool.

The CPS raises the cost of fossil-fuelled electricity generation. Figure 3.3 plots the 28-day moving average of the day-ahead prices for GB, France, and The Netherlands, as well as the price differences between the two connected markets. It also shows the variable cost (i.e. the short-run marginal cost) for Combined Cycle Gas Turbines (CCGTs) with 54.5%[5] thermal efficiency with EUA prices included (CPS excluded) as a measure of Continental gas generation costs.

GB prices were typically higher than Dutch prices but the CPS further widened the price difference between the two markets. French prices are much more volatile than the others mainly because nearly 80%[6] of its gross electricity generation comes from nuclear power stations (in 2015), making its electricity system less flexible and resulting in more volatile prices. Another reason for the high volatility is that French prices are very weather-sensitive given their high domestic electrical heating load. During Q3-Q4 2016 and Q4 2017, France experienced major nuclear outages, which explains the much higher French prices during those periods. The variable cost for CCGTs partially explains the patterns of prices for the three markets, and best fits the dynamics of the Dutch price, where gas is the marginal fuel most of the time.

[5] Measured at Lower Heating Value (LHV).
[6] See Eurostat.

3.3 A model of the cost of trade distortion

Consider two EU countries H (Home country, GB) and F (Foreign country) connected via an interconnector with capacity K. Without the CPS (but with the EUA price), wholesale electricity prices in each country are initially p_0^i, $i = \{H, F\}$ (subscript $j = 0$ indicates without the CPS, and 1 with the CPS). The net import to H over the interconnector is m_j ($-K \leq m_j \leq K$). Applying the CPS ($\tau > 0$) in H raises its wholesale price by Δp^H. The higher price in H induces more net imports ($\Delta m \geq 0$), which further changes generation in each country, with impacts on marginal costs in H and F and in turn wholesale prices. Our first aim is to estimate Δp^H, Δm and p_0^i, $i = \{H, F\}$,[7] with the estimate of Δp^H further informing us about the CPS pass-through rate to H's wholesale prices.

Demand is assumed inelastic in the short-run. Because changes in prices and imports have no obvious impact in that hour's intermittent renewable[8] and nuclear power generation, residual demand (total demand minus renewable and nuclear generation) does not change with the carbon price. Therefore, increased net imports imply the same reduction (increase) in fossil generation in H (F).[9] These supply changes, given the asymmetry in carbon taxes, will have first order welfare effects. Our second aim to measure this welfare loss.

The changes in trading patterns potentially influence emissions in H and F, with implications for global emissions and welfare. The third aim is to estimate the carbon leakage of the CPS via interconnectors, as well as the total CO_2 emission reduction and its associated monetary value (in a world where individual country changes lead to global changes).[10]

3.3.1 The CPS cost pass-through

The CPS raises short-run marginal costs of electricity generation, but generators in H may absorb some of the tax by marking up their offers by a smaller or larger amount if the market is imperfectly competitive, depending on the shape of the residual demand curve. In this case and in the absence of any cross-border trade, the cost pass-through of the CPS would

[7] p_1^i, $i = \{H, F\}$ are observed. Note $p_0^H + \Delta p^H \geq p_1^H$, because Δp^H measures the effect of the CPS on H's wholesale price with the net import fixed at m_0, while p_1^H is H's wholesale price after considering the change in net import Δm.

[8] Increased exports might allow an increase in constrained-off surplus wind, but these are only likely when the country is already exporting and limited by interconnector capacity.

[9] In the very short run, it may induce changes in the pattern of storage, but assuming that storage is efficiently used over the course of the day its total will not change and so will not affect the argument.

[10] The Market Stability Reserve removes the surplus EUAs, making reduction by one country effectively a reduction of global CO_2 emissions. Given this, the EU ETS operates as a carbon tax, for which this assumption would be valid.

then differ from 100%. Under proportional mark-up pricing (Newbery [103]), any cost shock would also be marked up, and the cost pass-through would be more than 100%.

Our post-econometric analysis allows us to estimate Δp^H, the increase in the GB wholesale price when no trading takes place. This enables us to measure the domestic cost pass-through as a percentage of the system marginal cost increase. A pass-through rate significantly different from 100% would cast doubt on the competitive assumption and possibly change domestic deadweight losses as output responds to the CPS. We put this to one side for the moment.

Algebraically, in a closed competitive market, assume that coal and gas are the only marginal fuels. At the margin, the short-run marginal costs (SRMC) of generating electricity from coal and gas (the EUA cost included) are c_C and c_G respectively, assumed unchanged by the CPS. Without the CPS, if the marginal share of coal is α_0, the electricity price in H is the system SRMC:

$$p_0^H = \alpha_0 c_C + (1-\alpha_0)c_G. \tag{3.1}$$

The CPS (τ, €/tCO_2) raises the system SRMC. If τ switches the merit order and hence the marginal share of fossil fuels, H's system SRMC with τ is

$$p_1^H = \alpha_1(c_C + e_C \cdot \tau) + (1-\alpha_1)(c_G + e_G \cdot \tau), \tag{3.2}$$

where α_1 is the marginal share of coal with the CPS, and e_C and e_G are emissions per megawatt hour of electricity (MWh_e) generated by marginal coal and gas. In this closed competitive market, the CPS has raised the electricity price by

$$\begin{aligned} p_1^H - p_0^H &= \tau \cdot [\alpha_1 \cdot e_C + (1-\alpha_1) \cdot e_G] + (c_C - c_G) \cdot (\alpha_1 - \alpha_0) \\ &= \tau \cdot \mu_1^H + (c_C - c_G) \cdot \Delta\alpha, \end{aligned} \tag{3.3}$$

where $\mu_1^H = [\alpha_1 \cdot e_C + (1-\alpha_1) \cdot e_G]$ denotes the Marginal Emission Factor (MEF) of H with the CPS applying, and $\Delta\alpha = \alpha_1 - \alpha_0$ is the change in the marginal share of coal.

Equation (3.3) suggests that if the CPS does not change the marginal share of coal and $\Delta\alpha = 0$, or if the SRMCs of coal and gas are close without the CPS and $c_C - c_G \approx 0$, the impact of the CPS on the domestic electricity price would be $\mu_1^H \cdot \tau$. Otherwise, given that normally coal is the cheaper fuel without the CPS ($c_C - c_G < 0$), and that from Chapter 2 the marginal share of coal has decreased with the CPS ($\Delta\alpha < 0$), the impact of the CPS on the electricity price should be higher than $\mu_1^H \cdot \tau$. Using the data and results from 2, we can estimate both $(c_C - c_G)$ and $\Delta\alpha$, which enables us to further examine whether the CPS has been fully passed through to the GB's wholesale electricity price.

3.3.2 Impact on electricity trade

Interconnectors complicate this simple single market story. Without capacity limits, the increase in H's electricity price will change flows until the prices in both markets equate. With capacity limit and if flows do not change due to an existing capacity constraint, there will be no additional distortion. However, if flows do change, there will be additional deadweight losses. If demand is inelastic, the deadweight loss will be the difference in the total cost of generation with and without the CPS.

We use geometric expositions[11] to clarify the problem, and distinguish five possible Cases of trade:

(a) trade is constrained without the CPS but is unconstrained with the CPS (H exports without the CPS): $p_0^H < p_0^F$ and $p_1^H = p_1^F$;

(b) trade is constrained with and without the CPS, but the direction of trade changes: $p_0^H < p_0^F$ and $p_1^H > p_1^F$;

(c) trade is unconstrained with and without the CPS: $p_j^H = p_j^F$;

(d) trade is unconstrained without the CPS but constrained with the CPS: $p_0^H = p_0^F$ and $p_1^H > p_1^F$;

(e) trade and its direction are unaffected by the CPS, as it is constrained by interconnector capacity: $p_j^H > p_j^F$, or $p_j^H < p_{jF}$.

Figure 3.4 gives a geometric exposition of Case (a). Without the CPS, H's net supply curve[12] is represented by s_0^H and F's supply curve is represented by s_0^F. H exports to F at the full interconnector capacity $m_0 = -K$, with H's prices (p_0^H) lower than F's prices (p_0^F) and congestion income equalling to $R_0 = (p_0^H - p_0^F) \cdot m_0$, or the rectangle AGHF.[13] Under the assumption of zero consumer demand elasticity (i.e. vertical demand curves), the interconnector creates an initial surplus (gains from trade) which is entirely due to a reduction in F's generation costs (the area under F's net supply curve from D to F), offset by an increase in H's cost (the area under H's net supply curve from C to A), or the area of the trapezium ACDF, made up of importer's and exporter's surplus (triangles DFH and ACG, respectively) and the congestion income without the CPS (rectangle AGHF). Given the slopes

[11] Similar analysis can be found in, for example, Newbery [102] and Fowlie [66].

[12] The supply from fossil fuels.

[13] The congestion income is the arbitrage gain from buying low and selling high, defined as the product of the interconnector flow and price difference between H and F.

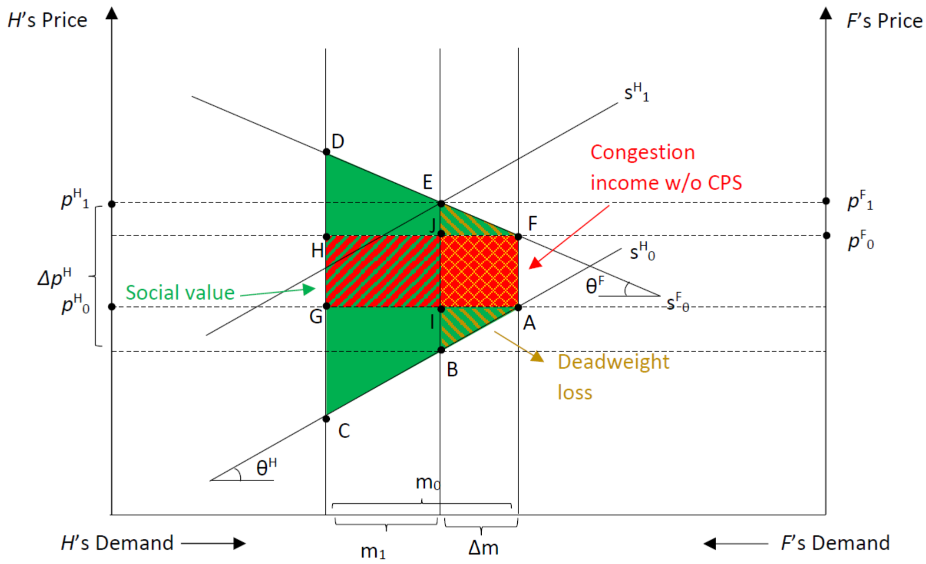


Fig. 3.4 Impact of CPS on imports and deadweight losses, Case (a)

of the net supply curves are, over the relevant range, θ^H and θ^F respectively for H and F, the social value of trade (when there is nothing to distort trade) is thus

$$S = \frac{1}{2} \cdot (\theta^H + \theta^F) \cdot m_0^2 + m_0 \cdot (p_0^H - p_0^F). \tag{3.4}$$

With the CPS, H's supply curve shifts upward to s_1^H. Although H is still exporting, the interconnector is now uncongested and the net import increases by Δm. The deadweight loss is defined as the difference between F's increased generation cost (the area under F's net supply curve from F to E) and H's reduced generation cost (the area under H's net supply curve from A to B). Given θ^H and θ^F, the deadweight loss L is the trapezium ABEF, made up of triangles EFJ and ABI and rectangle AIJF. Algebraically,

$$L = \frac{1}{2} \cdot (\theta^H + \theta^F) \cdot \Delta m^2 + \Delta m \cdot (p_0^F - p_0^H). \tag{3.5}$$

In this case, there is no congestion income with the CPS applying, so the change in congestion income is

$$\Delta R = (p_1^F - p_1^H) \cdot m_1 - (p_0^F - p_0^H) \cdot m_0, \tag{3.6}$$

where in this case, $p_1^F - p_1^H = 0$.

In Case (b)-(e) similar arguments apply. The social value of the interconnector is due to a reduction in the importer's generation costs offset by an increase in the exporter's cost where there is no trade distortion, and the deadweight loss is the difference between F's increased generation cost and H's reduced generation cost following the unilateral carbon tax. Finally, the congestion income is the product between price differences and flows. Appendix B.3 gives detailed expositions for each case.

To sum up, in all cases the social value can be expressed as equation (3.4), the deadweight loss from the trade distortion can be expressed as equation (3.5), and the change in congestion income can be expressed as equation (3.6). Given this, both the social value and deadweight losses are (linearly) positively correlated with the price difference where the CPS is not applied, and (quadratically) positively correlated with the interconnector capacity (which determines the magnitudes of m_0 and Δm). The change in congestion income would depend on flows and price differences with and without the CPS.

3.3.3 Global impact

The CPS has substantially reduced domestic CO_2 emissions from electricity. However, changes in trade between H and F could potentially undo some part of H's CO_2 emission reduction. For simplicity, we assume that the fuel mix and the marginal fuel shares abroad do not change with net exports (i.e. they are unaffected by the CPS). This would be plausible if there were no internal transmission constraints on the Continent, as changes in their exports would be a very small fraction of total generation. Given this, the foreign country's Marginal Emissions Factor[14] (MEF, μ^F) remains unchanged and the slope of its net supply curve is also unchanged. Also assume that the CPS has little short-run impact on non-EU countries other than through changing global emissions.

ΔW is the change in global welfare that increases from a fall in total emissions. If the Social Cost of Carbon (SCC)[15] is C, and deadweight loss is L defined in (3.5), then,

$$\Delta W = (\Delta E + \varepsilon) \cdot C - L, \tag{3.7}$$

where ΔE denotes the emission reduction due to changes in H's fuel mix (holding imports fixed), and ε denotes the emission reductions due to H's increased import from F. In Chapter 2, we use a unit commitment dispatch model to give estimates of GB's emission reduction from CPS in 2015 when holding imports fixed, while in this chapter we focus on the second part of emissions reduction, ε. With the CPS, the MEFs for H and F are μ_1^H and μ^F, so the

[14]The CO_2 released from the last unit of electricity generated in MWh/tonne CO_2.

[15]The SCC is defined as the present discounted social cost of the damage caused by emitting one tonne of carbon (more usually measured per tonne of CO_2).

emission reduction from trading is

$$\varepsilon = (\mu_1^H - \mu^F) \cdot \Delta m. \tag{3.8}$$

The next challenge is to identify the effective SCC. The US estimate ranges from $\$_{2018}14$/t$CO_2$ (5th percentile, uprated by the Commodity Price Index) to $\$_{2018}130$/t$CO_2$ (95th percentile) with an average at 3% discount rate of $\$_{2018}45$(€38)/t$CO_2$ (USEPA [150]). At the lower discount rate preferred by Stern [143] and many others, the SCC would be higher. The UK Government's figure for sectors not covered by the ETS (i.e. the full SCC) in 2020 was £$_{2018}$70 (€79)/tCO_2.[16]

The 2019 average GB carbon price for fossil generation was €45/tCO_2, greater than both the average United States (US) SCC and the EU ETS level of €20/tCO_2. Even if the 2019 GB price is considered a defensible SCC, from 2013 the annual average GB price has steadily risen from €8.23/tCO_2 at which level it would be considerably below the US SCC. In our analysis, to calculate the global surplus from the CPS, we take the 2019 British carbon price as the SCC, i.e. $C =$€45/tCO_2. Clearly it is simple to adjust ΔW for other values of the SCC, C.

3.3.4 Other distributional impacts

There are other distributional impacts from the CPS. As prices increase in both countries, some producers gain and consumers lose.[17] In the home country, the government receives additional tax revenue from the CPS, and both countries receive EUA revenues that change with output (as we are assuming the the *Market Stability Reserve* cancels excess allowances). Estimating these distributional impacts requires knowledge about market structures of both markets, and perhaps simulation techniques are preferable to econometric methods. We leave their estimation for future research.

3.4 Econometric Models

This section presents the econometric specifications to study the impact of the British CPS and interconnector flows on the domestic and foreign day-ahead electricity prices. Data availability[18] makes IFA, the interconnector between GB and France, the main focus, though

[16] See Forest Research

[17] H's marginal fossil suppliers may not gain from the higher domestic wholesale price but H's other suppliers such as wind and nuclear generators will gain.

[18] We are unable to obtain the Dutch day-ahead or actual wind and load data for the period before 2015.

we provide some less reliable estimates for BritNed, the electricity link between GB and the Nertherlands. The analysis runs from 4 February 2014, when the North-Western Europe market coupling went live, to 30 September 2018, when GB first became coupled with the island of Ireland. During this period, no new interconnectors were commissioned, and the capacity of fossil plants, especially coal, was stable in GB, France, and The Netherlands. Over the period, the British CPS rose from £4.94/tCO_2 to £9.55/tCO_2 and then stabilised at £18/tCO_2, providing a sufficient number of observations for different levels of the CPS. In this section, we present the simplest specification with neither peak and off-peak heterogeneity nor interaction terms. Section 3.6 gives the results and also examines heterogeneity between peak and off-peak and includes interaction terms.

One of our major challenges in estimating the impact of flows on electricity prices is that the day-ahead market is an implicit auction, which means the domestic and foreign prices and the interconnector flows are determined simultaneously, raising the issue of simultaneity. Finding proper instrumental variables for the day-ahead flows is difficult because under market coupling, the day-ahead flows are only determined by the day-ahead price differences, i.e. the dependent variables. To address this we use the marginal effects of wind on prices as proxies for the marginal effects of flows which should have similar impacts on fossil generation.

To deal with the very substantial electricity price volatility, we implement the Multivariate Generalised Auto-Regressive Conditional Heteroskedasticity (M-GARCH) model (Silvennoinen and Teräsvirta [141]), which accounts for variations in both the mean and volatility of electricity prices. M-GARCH has been widely used to model day-ahead electricity prices (e.g. Kirat and Ahamada [91], Annan-Phan and Roques [9]).

As hourly electricity prices in most European countries for the next day are all set simultaneously in the pan-European day-ahead auction, it would be problematic to treat them as univariate hourly time series. As all day-ahead hourly bids and offers are submitted at the same time, within that day the price for any hour carries little in any information about the next hour (Sensfuß et al. [137], Würzburg et al. [161], Keppler et al. [88]). Therefore, for each country we aggregate to give daily averaged day-ahead prices. The *mean equation* of the M-GARCH model is then

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \boldsymbol{\Gamma}\boldsymbol{X}_t + \boldsymbol{\varepsilon}_t, \;\; \boldsymbol{y}_t = \left(P_t^{GB}, P_t^{FR}\right)', \tag{3.9}$$

where $\boldsymbol{y}_t$ is a 2×1 vector of day-ahead GB and French prices, and t represents days. $\boldsymbol{X}_t$ is a $k \times 1$ vector of exogenous covariates, including the day-ahead forecast[19] of wind and nuclear

[19] Whenever the forecast data is unavailable, we use the actual data as a proxy.

generation for both countries, day-ahead forecast of electricity load (i.e. demand) for both countries, coal and gas costs, the EUA price, the day-ahead scheduled interconnector capacity and most importantly, the British CPS. We also include dummy variables representing the days of the week and the quarters of the year.[20]

We do not include auto-regressive terms of the dependent variables in the regression because first, the electricity wholesale markets in GB and France are workably competitive (CMA [42], Pham [123]). This means that bidding behaviour is primarily driven by the short-run marginal cost, instead of the market outcome from days before. Second, including day-of-week dummy variables allow us to effectively capture the difference in price patterns between weekdays and weekends. Lagged fuel costs and carbon prices are also excluded from the model as the experienced market participants can observe the daily prices of each before making their bids.

All covariates can be treated as exogenous. Wind generation depends on weather, and electricity load is inelastic to prices in the short-run (Clò et al. [40]). Nuclear generation is also exogenous as it runs unless an outage occurs.[21] Although some studies have found that dynamic interactions among fuel, carbon, and electricity prices may play an important role in price formation (Knittel and Roberts [92]), we argue that fuel and carbon costs (EUA prices in this case) are more likely to be affected by the EU-wide demand by the much larger covered sector for EUAs, a claim supported statistically in Chapter 4. They also find the exchange rate between Euro and Sterling is exogenous with respect to electricity prices. Finally, the scheduled interconnector capacity is only influenced by outages, maintenance or network limitations and so can also be treated as exogenous.

We expect wind and nuclear generation to reduce electricity prices and load to raise prices. As GB has consistently been a net importer of electricity from the Continent, we expect interconnector capacity to lower the GB price and raise foreign prices. We also expect the fuel costs and EUA prices to raise electricity prices, and the magnitude of the impacts depends on the (marginal) fuel mix in the market. From Chapter 2, during 2013-2017 fossil fuel provided more than 80% of GB's marginal generation, while the marginal generation in France has heavily relied on hydro and imports. Therefore, one might expect fuel costs and EUA prices to have a stronger impact on the GB price than the French price. However, marginal imports of France come from in other fossil-fuel intensive Continental markets (e.g.

[20] The yearly dummy variables are not included mainly because it can substantially save computational time, especially for the more complicated specifications such as Regression (iii) in Table 3.2. Also, almost all covariates carry information of (yearly) trends and drifts (if any), which weakens the importance of the yearly dummies. Lastly, including yearly dummies in the regressions have negligible effects on the estimation results.

[21] Although the French nuclear power may reduce output off-peak, aggregating the hourly observations to daily can effectively deal with the potential endogeneity.

Germany, Belgium, Spain and Italy), which could also influence the French price, potentially boosting the effect of fuel costs and EUA prices on the French price.

Our estimates of the impact of the CPS on the prices are conditional on interconnector capacity but *unconditional* on interconnector flows, meaning that the coefficients for the CPS can only be interpreted as the estimates of the diluted (by trade) impact of the CPS on both GB and French prices. As other EU countries have not yet introduced a carbon tax similar to the CPS, the higher GB carbon tax result in foreign countries exporting more electricity to GB, which in turn lowers the GB price and raises the foreign price. We therefore expect the CPS to have positive impacts on both GB and French prices, though its effect on the GB price should to be much higher.

To control for dynamic heteroskedasticity, we assume $\boldsymbol{\varepsilon}_t$ to be conditionally heteroskedastic. We use the Constant Conditional Correlation (CCC)[22] GARCH(1,1) model proposed by Bollerslev [18], where the conditional correlation matrix, $\boldsymbol{H}_t$, can be expressed as:

$$\boldsymbol{H}_t = \boldsymbol{D}_t^{1/2} \boldsymbol{R} \boldsymbol{D}_t^{1/2}, \tag{3.10}$$

where $\boldsymbol{R} = [\rho_{ij}]$ is a 2×2 time-invariant covariance matrix of the *standardised* residuals $\boldsymbol{D}_t^{-1/2} \boldsymbol{\varepsilon}_t$. $\boldsymbol{R}$ is positive definite with diagonal terms $\rho_{ii} = 1$. $\boldsymbol{D}_t = [d_{ij,t}]$ is a diagonal matrix consisting of conditional variances with $d_{ii,t} = \sigma^2_{ii,t}$, and $d_{ij,t} = 0$ for $i \neq j$.

The model assumes the conditional variances for electricity prices follow a univariate GARCH(1,1) process and the covariance between prices is given by a constant-correlation coefficient multiplying the conditional standard deviation of the price differentials:

$$\sigma^2_{ii,t} = s_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i \sigma^2_{ii,t-1}, \tag{3.11}$$

$$\sigma^2_{ij,t} = \rho_{ij} \sqrt{\sigma^2_{ii,t} \sigma^2_{jj,t}}, \tag{3.12}$$

where s_i is a constant term, α_1 is the ARCH parameter capturing short-run persistence and β_1 is the GARCH parameters capturing long-run persistence.

One advantage for the M-GARCH model is that it allows for the existence of missing data, where the missing dynamic components are substituted by the unconditional expectations. The model is estimated by Maximum Likelihood Estimation.

[22] The Wald test suggests to use the CCC model instead of a more complicated Dynamic Conditional Correlation (DCC) model, and both models provide very similar estimation results.

3.5 Data

Table 3.1 gives summary statistics for all variables. The day-ahead price for France is collected from Epex Spot, and the day-ahead price for GB comes from the Nord Pool Market Data Platform. The French System Operator (RTE) provides forecasts of hourly French electricity load and wind generation, as well as the actual hourly French nuclear generation. While we are unable to find the day-ahead forecast of GB load and wind generation over the whole period, we use the actual half-hourly data from National Grid as proxies. The half-hourly GB nuclear generation is collected from the Elexon portal. ENTSO-E provides the day-ahead forecasted transfer capacity of interconnectors. All (half-)hourly data are aggregated to daily averages.

Table 3.1 Summary Statistics

Variable	Unit	Abbr.	Mean	S. D.	Min.	Max.
GB day-ahead price	€/MWh	P^{GB}	53.80	9.72	33.33	199.98
French day-ahead price	€/MWh	P^{FR}	39.86	14.82	2.98	125.92
IFA day-ahead capacity	GW	IC^{IFA}	1.77	0.38	0.43	2.00
GB load	GW	D^{GB}	31.31	4.44	20.82	42.91
French load	GW	D^{FR}	53.36	10.62	34.82	87.97
GB wind	GW	W^{GB}	2.97	1.92	0.14	10.16
French wind	GW	W^{FR}	2.28	1.49	0.33	10.54
GB nuclear	GW	W^{GB}	7.32	0.76	4.25	8.99
French nuclear	GW	W^{FR}	44.93	6.37	29.94	60.61
CPS	€/tCO_2	CPS	19.36	4.99	5.88	26.06
Coal plant var. cost	€/MWh$_e$	VC^{COAL}	28.19	4.48	17.44	37.79
Gas plant var. cost	€/MWh$_e$	VC^{CCGT}	34.50	6.75	20.29	54.47
EUA price	€/tCO_2	EUA	7.61	3.58	3.99	25.19

The daily UK National Balancing Point (NBP) price[23] and the EUA price are collected from the InterContinental Exchange, and the daily coal price is collected from the CME group, representing coal prices at global level. In order to count in the transportation cost of coal into power stations, quarterly averages of the daily prices are subtracted from the BEIS quarterly

[23] An alternative is to use the Dutch natural gas price at the Title Transfer Facility (TTF) Virtual Trading Point. However, as the European natural gas markets are rather liquid, the two natural gas prices are extremely close.

3.6 Results

In our regressions, outliers for day-ahead electricity prices are defined as values exceeding four standard deviations of the sample mean and are removed and treated as missing data. Wald tests examine whether the more complicated Dynamic Conditional Correlation (DCC) models instead of the proposed Constant Conditional Correlation (CCC) models are necessary (Tse and Tsui [148]), and the test statistics suggest using CCC models. Table 3.2 presents the estimation results of the mean equations.[24]

Regression (i) ignores the heterogeneity between peak and off-peak behaviour. We find the estimated impact of the CPS on the French price is unexpectedly high: a €1/tCO_2 increase in the CPS is associated with a €0.32/MWh increase in the French price, more than a half of its impact on the GB price. Further analysis reveals that even though we have controlled for nuclear generation, the major French nuclear outages (in Q3-Q4 2016 and Q4 2017) have much higher effects on the French prices than during normal outages, and ignoring this effect would result in omitted variable bias.

As a result, in Regressions (ii) and (iii) we add a dummy variable representing periods of major French nuclear outages. Regressions (ii) and (iii) also separates the day into peak and off-peak, hence the vector of dependent variable $\boldsymbol{y}_t$ now becomes a 4×1 vector $(P_t^{GB,P}, P_t^{FR,P}, P_t^{GB,O}, P_t^{FR,O})'$, namely the daily averaged peak and off-peak electricity prices for GB and France. Peak and off-peak have different demands and fuel mix, so the marginal fuel could differ, resulting in different marginal effects on electricity prices. Regression (iii) further adds interaction terms between some of the existing covariates and a dummy variable equalling to one when the British CPS was stabilised at £18/tCO_2 (after April 2015). This is because the high CPS has switched the merit order between coal and gas within the GB electricity dispatch (see Chapter 2), hence after April 2015, wind might displace different fuel types and have different effects on the GB price. For the same reason, the marginal effects of fuel costs and EUA prices on the GB price could be different before and after April 2015.

From Regressions (ii) and (iii), we find evidence on both domestic and foreign wind lowering French prices, in agreement with Annan-Phan and Roques [9]. The intuition is that higher foreign wind reduces foreign electricity prices, resulting in higher domestic net import, which further reduces domestic prices. Although Regression (ii) suggests French wind has a positive effect on the GB price during peak periods, the magnitudes are small and the effect disappears in Regression (iii).

[24] The full results are listed in Table B.1.

Table 3.2 M-GARCH results

	Unit	(i)	(ii)		(iii)	
GB DAM prices			Off	Peak	Off	Peak
GB wind	GW	-0.881^{***}	-0.410^{***}	-0.965^{***}	-1.162^{***}	-0.826^{***}
		(0.039)	(0.055)	(0.036)	(0.113)	(0.078)
GB wind ×CPS Dummy	GW				0.873^{***}	-0.221^{*}
					(0.114)	(0.086)
French wind	GW	-0.054	-0.219^{***}	0.153^{***}	-0.210^{***}	0.056
		(0.049)	(0.063)	(0.038)	(0.057)	(0.043)
IFA capacity	GW	-0.836^{***}	-0.071	-2.553^{***}	0.134	-1.896^{***}
		(0.241)	(0.203)	(0.145)	(0.183)	(0.207)
Coal price	€/MWh$_e$	0.345^{***}	0.426^{***}	0.336^{***}	0.429^{***}	0.053
		(0.021)	(0.024)	(0.016)	(0.069)	(0.056)
Coal price ×CPS Dummy	€/MWh$_e$				-0.145^{*}	0.335^{***}
					(0.063)	(0.056)
Gas price	€/MWh$_e$	0.825^{***}	0.702^{***}	0.945^{***}	0.609^{***}	0.930^{***}
		(0.015)	(0.019)	(0.015)	(0.034)	(0.034)
Gas price ×CPS Dummy	€/MWh$_e$				0.201^{***}	-0.114^{**}
					(0.041)	(0.043)
EUA	€/tCO_2	0.507^{***}	0.554^{***}	0.409^{***}	0.994^{***}	1.039^{***}
		(0.024)	(0.029)	(0.024)	(0.214)	(0.175)
EUA ×CPS Dummy	€/tCO_2				-0.479^{*}	-0.565^{**}
					(0.219)	(0.178)
CPS	€/tCO_2	0.595^{***}	0.545^{***}	0.633^{***}	0.366^{***}	0.584^{***}
		(0.013)	(0.018)	(0.015)	(0.055)	(0.046)
French DAM prices						
GB wind	GW	-0.135	-0.226^{**}	-0.131	-0.238^{**}	-0.146^{*}
		(0.076)	(0.081)	(0.070)	(0.081)	(0.070)
French wind	GW	-1.817^{***}	-1.896^{***}	-1.467^{***}	-1.898^{***}	-1.485^{***}
		(0.089)	(0.092)	(0.083)	(0.092)	(0.083)
IFA capacity	GW	-0.674	-1.505^{***}	-1.047^{**}	-1.465^{***}	-0.942^{**}
		(0.379)	(0.314)	(0.357)	(0.312)	(0.359)
Coal price	€/MWh$_e$	0.607^{***}	0.531^{***}	0.494^{***}	0.516^{***}	0.482^{***}
		(0.035)	(0.043)	(0.043)	(0.043)	(0.043)
Gas price	€/MWh$_e$	0.690^{***}	0.317^{***}	0.550^{***}	0.323^{***}	0.538^{***}
		(0.037)	(0.036)	(0.037)	(0.036)	(0.038)
EUA	€/tCO_2	0.611^{***}	0.979^{***}	0.913^{***}	1.005^{***}	0.949^{***}
		(0.060)	(0.064)	(0.069)	(0.063)	(0.068)
CPS	€/tCO_2	0.320^{***}	0.046	0.098^{*}	0.050	0.103^{**}
		(0.039)	(0.037)	(0.039)	(0.037)	(0.039)
Nuclear outage			5.932^{***}	7.535^{***}	6.247^{***}	7.886^{***}
			(0.581)	(0.682)	(0.580)	(0.695)
No. Obs.		1687	1684		1684	

Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

"Coal price" and "Gas price": the short-run marginal cost excluding carbon prices.

We find interconnector capacity of IFA reduces electricity prices in GB, as GB is consistently a net importer from France. The effects are significantly different between peak and off-peak, probably because GB has a convex and monotonically increasing marginal cost curve. During off-peak periods, the demand is low and the electricity system is running at base load with a relatively flat marginal cost curve, so a change in the interconnector capacity (hence import) has little effect on the GB price.

Counterintuitively, we find interconnector capacity has a negative effect on French prices as well, for rather complicated reasons. On the one hand, 80% of the French electricity comes from nuclear power stations with close-to-zero marginal costs, and the French electricity market is designed to be an exporter of electricity. Therefore, when the French nuclear stations are dispatching with full capacity, its electricity supply curve is mostly flat. On the other hand, when France is importing, it is likely because of high demand relative to nuclear output (cold weather, nuclear outages). In those cases, due to its limited capacity of fossil fuels, the French marginal cost curve can be steep where it meets demand, and importing (or increasing interconnector capacity) can substantially reduce the French electricity price. As a result, one may observe interconnector capacity substantially reducing the French prices, even though France exports to GB most of the time. This is not the case between BirtNed's capacity and the electricity price of The Netherlands, who has a much smaller share of nuclear capacity in its electricity system, as illustrated in Appendix B.4.4.

Electricity prices are positively correlated with both coal and gas costs. However, gas costs are found to have a much stronger impact in GB than France because the GB electricity system relies more heavily on gas. This is especially the case after April 2015, when the CPS has made the GB electricity supply less coal-dependent and more gas-dependent, while in France coal remains relatively cheaper. For both countries, the marginal effects of gas costs are significantly higher in peak than off-peak periods, consistent with the results in Chapter 2, where we argue that because peak demand is more variable, the more flexible gas plants are preferred to respond to wind and demand changes.

As GB's electricity generation is less carbon intensive thanks to the CPS, the EUA price has positive but smaller effects on the GB price than the French price (well-connected to a fossil hinterland). The CPS has a positive impact on the French price, consistent with GB importing more electricity from France due to the CPS.

From regression (iii), the marginal effects of wind, fuel costs, and EUA prices are substantially different before and after the 2015 rise in the CPS. Before then, wind had a very substantial effect on GB's off-peak prices, while the high CPS made it less influential, suggesting a much flatter marginal cost off-peak schedule after April 2015. Because the high CPS has switched coal from base to the mid-merit load, coal costs are expected to have a stronger impact on the peak than off-peak GB prices, and *vise versa* for gas costs. Our regression results are in agreement with the theory and find that since April 2015, GB prices rely more heavily on coal costs during peak periods and more heavily on gas costs during off-peak periods.

Both regression (ii) and (iii) suggest that during nuclear outages, the French price is about €6/MWh higher than usual in off-peak periods. The number is slightly high in peak periods at about €7.7/MWh.

In the rest of this section, Subsections 3.6.1-3.6.3 utilises results from Regression (iii) to estimate the counterfactual (i.e. with the CPS not applying) prices and flows of GB and France, the CPS pass-through to the GB electricity price, and the trade distortion between GB and France. Subsection 3.6.4 discusses the global impact of the CPS, and Subsection 3.6.5 gives a summary of BritNed, the interconnector between GB and The Netherlands.

3.6.1 Estimating the counterfactual IFA flows

Table 3.2 gives the estimated impacts of wind and the CPS on the GB and French electricity prices for both peak and off-peak periods. Appendix B.4.1 shows how the estimates from Regression (iii) give the counterfactual prices and flows.

Table 3.3 summarises the average annual (electricity year from 1 April to 31 March) day-ahead electricity prices of GB and France, GB's net import, and congestion income. The differences between the actual and the counterfactual cases are also listed (in the columns denoted with Δ). The counterfactual for the electricity year 2014-2015 removes the CPS of £9.55/tCO_2, while the counterfactual for the electricity years 2015-2018 removes the CPS of £18/tCO_2. The final rows give the averages over 2015-2018.

The CPS increases the GB price and hence net imports, which mitigates the GB price rise somewhat and (slightly) increases the French price. Over 2015-2018, the £18/tCO_2 of CPS has on average raised the GB price by €11.43/MWh (or by 28%) and the French price by €1.37/MWh (or 3.5%) [25] Perhaps unexpectedly, without the CPS, GB's net imports for IFA during 2016-2018 would be close to zero, as the electricity prices between the two countries would be close, caused by French nuclear outages in both winters of 2016 and 2017 and the associated high French prices. During 2015-2018, GB in total imported 23 TWh more electricity from France as a result of the CPS, or about 65% of its actual net import from France. Finally, because the CPS widened the price difference between the two countries, congestion income has risen by €95 m/yr over 2015-2018. This congestion income mostly

[25] This means, on average, a €1/tCO_2 increase in the CPS is associated with a €0.06/MWh increase in the French price, consistent with our estimates in Table 3.2. Therefore, it is perfectly reasonable to assume that the CPS has no direct impact on the French price other than through trading via IFA in Step 2 of Appendix B.4.1.

Table 3.3 IFA: the counterfactual prices, flows, and congestion income

Electricity	**GB Prices (€/MWh)**			**French Prices (€/MWh)**		
years	w. CPS	w/o CPS	Δ	w. CPS	w/o CPS	Δ
14-15	€52.22	€46.20	€6.02	€36.39	€35.69	€0.70
		(0.44)	(0.44)		(0.06)	(0.06)
15-16	€53.24	€40.40	€12.85	€34.49	€33.24	€1.25
		(0.88)	(0.88)		(0.14)	(0.14)
16-17	€51.76	€40.70	€11.06	€43.22	€41.93	€1.29
		(0.77)	(0.77)		(0.12)	(0.12)
17-18	€52.70	€42.31	€10.39	€42.21	€40.63	€1.58
		(0.71)	(0.71)		(0.14)	(0.14)
Ave.(15-18)	€52.57	€41.14	€11.43	€39.97	€38.60	€1.37
		(0.78)	(0.78)		(0.13)	(0.13)
	GB Net Import (TWh)			**Congestion Income (m€)**		
	w. CPS	w/o CPS	Δ	w. CPS	w/o CPS	Δ
14-15	15.21 TWh	11.29 TWh	3.92 TWh	€243	€164	€79
		(0.33)	(0.33)		(5.04)	(5.04)
15-16	15.52 TWh	8.55 TWh	6.97 TWh	€303	€143	€160
		(0.75)	(0.75)		(7.82)	(7.82)
16-17	8.17 TWh	1.05 TWh	7.12 TWh	€185	€130	€55
		(0.61)	(0.61)		(1.44)	(1.44)
17-18	11.32 TWh	2.57 TWh	8.75 TWh	€194	€123	€70
		(0.75)	(0.75)		(2.75)	(2.75)
Ave.(15-18)	11.67 TWh	4.60 TWh	7.61 TWh	€227	€132	€95
		(0.70)	(0.70)		(3.76)	(3.76)

Standard errors in parentheses.

comes from British consumers, and half of it is transferred to France, because the electricity system operator of French owns half of IFA.

3.6.2 The CPS pass-through to the GB day-ahead price

The CPS increases the cost of electricity generation and raises GB's day-ahead prices. In a closed competitive economy, the ratio between the increase in the GB price and the increase in the system marginal cost (due to the CPS, holding interconnector flows constant) is the CPS pass-through to the GB day-ahead price.

Appendix B.1 gives details on how we estimate the CPS pass-through rate. Our estimation suggests that the CPS pass-through rate to GB's peak prices was 173% with a 95% confidence interval of 147-200%, and to GB's off-peak prices was 72% with a 95% confidence interval of 47-96%. The weighted average was 133% with a 95% confidence interval of 108-159%. The higher cost pass-through in peak periods compared to off-peak is consistent with most empirical literature (e.g. Sijm et al. [140], Jouvet and Solier [86], Fabra and Reguant [56]). In Chapter 4, we explain this as electricity utilities strategically bid a lower rate than the short-run marginal cost during off-peak periods to stay dispatching to avoid the much higher shut-down and re-start costs. On the other hand, to compensate the off-peak losses, utilities need to bid a higher rate than the short-run marginal cost during peak periods, as high demand and reduced residual capacity allow them to exercise some market power.

Although we reject the null hypothesis that the average cost pass-through of the CPS is 100% at 5% significant level, if we have under-estimated the individual fuel emissions factors, our cost-pass through rates would be over-estimated. Fabra and Reguant [56] are unable to reject full pass-through except for off-peak hours, using more detailed micro-data than this study.

3.6.3 Market distortion from IFA

We can use the counterfactual prices and flows estimated in Section 3.6.1 to further estimate IFA's social value from trading and deadweight losses from asymmetric carbon taxes, as discussed in Section 3.3.2. In addition, we also estimate the UK Government's losses in carbon-tax revenue from the GB generation displaced by increased imports over IFA. (Details are presented in Appendix B.4.2.)

Table 3.4 IFA: surplus, distortion and losses

Electricity years	**Social Value (m€)**	**Deadweight Loss (m€)**	**GB CPS Rev. Loss (m€)**
14-15	€209	€13.4	€20.2
	(5.27)	(2.10)	(1.74)
15-16	€187	€39.8	€69.7
	(8.03)	(7.23)	(7.52)
16-17	€164	€41.5	€55.7
	(1.51)	(6.32)	(4.99)
17-18	€167	€46.0	€61.2
	(2.95)	(7.58)	(5.37)
Ave. 15-18	€173	€42.4	€62.2
	(3.80)	(7.04)	(5.93)

Standard errors in parentheses.

Table 3.4 lists the social value, deadweight loss, and carbon-tax revenue loss. During 2015-2018, the average deadweight loss from the trade distortion was €42.4 m/yr, about

24% the average social value (€173 m/yr). The average loss in the CPS tax revenue was €62.2 m/yr in the case of IFA, or about 6% of the 2017 CPS tax receipts.

3.6.4 Carbon leakage and the impact on global welfare via IFA

From Section 3.3.3, IFA's carbon emission reduction from the high import (ε) is determined by the difference of the MEF between GB and France ($\mu_1^H - \mu^F$) and the change in GB's imports from France (Δm). Appendix B.4 estimates the MEF for France is $\hat{\mu}^F = 0.46$, and Chapter 2 provides the MEF for GB is $\hat{\mu}_1^H = 0.38$. Then, the carbon leakage to France is about 3.5 (=0.46×7.61) mtCO_2/yr. In total, IFA has emitted roughly 0.6=$[(0.46 - 0.38) \times 7.61]$ million tonnes more CO_2 per year due to the higher GB import. If we take the British carbon price in 2019 as the social cost of carbon (C=€45/tCO_2), the social cost of these increased emissions is about €27 million.

In Chapter 2, we run a unit commitment dispatch model of the 2015 GB power system to estimate that the £18/tCO_2 CPS reduces emission by 44.5 mtCO_2/year. Thus about 1.3% of the CO_2 emission reduction from the CPS is undone by France. Then, from equation (3.7), the estimated total increase in global welfare from the CPS is about €2 bn/yr, hence the distortion from IFA trade (i.e. the deadweight loss caused by the CPS) is only about 2% of this welfare change.

3.6.5 BritNed: the interconnector between GB and The Netherlands

Appendix B.4.4 gives estimates of the impact of the CPS and wind on the GB and Dutch electricity prices, and the estimated counterfactuals for BritNed. During electricity years 2015-2018, the CPS on average raised the Dutch wholesale price by €1.02/MWh, or 2.8%. About 63% (4.77 TWh) of GB's actual net import from The Netherlands was due to the CPS, and congestion income almost doubled (from €59 m/yr to €117 m/yr). The social value of BritNed was about €77 m/yr, and the deadweight loss from unilateral carbon taxes was €39 m/yr, about half of the social value and about the same size of the IFA loss (which is twice the capacity). The UK Government lost about €39.2 million in carbon tax revenue, about 4% of its total CPF receipts in 2017.

Carbon leakage to The Netherlands is about 1.6 mtCO_2/yr. Since gas is the marginal fossil fuel in The Netherlands, BritNed's total emission has actually reduced by 0.2 mtCO_2/yr compared with the zero CPS scenario. This reduction of CO_2 emission is worth about €9 m/yr, partly offsetting the increase in IFA's total emission.

3.7 Conclusions and Policy Implications

Unilateral carbon taxes distort trade if they alter interconnector flows, resulting in deadweight losses. In all cases, asymmetric carbon taxes transfer revenue abroad at a cost to the domestic economy.

This chapter investigated the impact of such carbon taxes on cross-border trade of electricity, theoretically, geometrically and empirically, and discussed their global impact. Empirically, taking the British Carbon Price Support (CPS, an additional carbon tax) as a case study, we estimate the counterfactual (without the CPS) electricity prices and flows of the connected countries, and further examine the impact of the CPS on GB's net import and congestion income. In addition, we also estimate the social value from cross-border electricity trading, the deadweight loss from asymmetric carbon taxes, the carbon leakage due to untaxed imports, and the global emissions impact of the CPS.

Our estimates show that during electricity years 2015-2018, the CPS increased the GB day-ahead price by €11.43/MWh (about 28% of the GB wholesale price) after allowing for displacement by cheaper imports. The CPS increased imports by 7.6 TWh/yr from France and by 4.8 TWh/yr from The Netherlands (in total, about 4% of the GB annual electricity demand), thereby reducing carbon tax revenue by €62 m/yr from IFA and by €39 m/yr from BritNed (in total, about 10% of the 2017 CPS tax receipts). Congestion income for IFA was increased by €95 m/yr and for BritNed's by €58 m/yr (in total, by 80% relative to the zero CPS case). The social value of interconnector was around €173 m/yr for IFA and €77 m/yr for BritNed, but the deadweight loss due to the CPS was €42 m/yr for IFA and €39 m/yr for BritNed. In total, the deadweight loss from the CPS accounted for 4% of the global welfare gain from the CPS (mainly from reduced coal burn in GB) at €2 billion/yr. The CPS also raised the French wholesale price by 3.5% and the Dutch wholesale price by 2.8%. As foreign electricity did not bear a CPS (and still does not), imports from France undid 1.3% of the CO_2 emission reduction partly compensated by -0.4% from The Netherlands (adding to net 0.9%), and the net social cost of this leakage was about €18 m/yr.

The increase in congestion income (mostly) comes from GB electricity consumers but is equally allocated to both Transmission System Operators as owners of the interconnectors. This increased congestion income could over-incentivise further investment in additional interconnectors, at least to carbon-intensive markets lacking such carbon taxes. The increase in French and Dutch day-ahead prices raised their producer surplus but increased consumer electricity costs. The objective of the British CPS was to reduce British CO_2 emissions and incentivise low-carbon investment, but this was partly subverted by increased imports of more carbon-intensive electricity from the Continent. Finally, asymmetric carbon taxes incur modest, but non-negligible deadweight losses, resulting in less efficient cross-border trading.

Although the UK formally departed from the EU, at the time of writing there are three interconnectors (between the UK and the Continent) under construction and two more in early development. More interconnectors would, of course, further distort the market. Although the social value of interconnectors would also increase, the deadweight loss tends to increase as the square of the distorted flow, hence the benefit from extra interconnectors tends to fall.

Despite the CPS distorting cross-border electricity trading, it has significantly reduced GB's greenhouse gas emissions from electricity generation, with its coal share fall from 35% in 2015 to less than 3% in 2019. On 21 April 2017, GB power generation achieved the first-ever coal-free day. When the UK introduced the CPF, the hope was that other EU countries would follow suit to correct the failures of the Emissions Trading System. As the electricity sector in most countries is the cheapest source of reducing CO_2 emissions and as carbon taxes are the an attractive way to reduce the distorting cost of raising tax revenue, the case for an EU-wide carbon price floor are clear. This case is further strengthened by the desirability of correcting trade distortions.

Chapter 4

Cost Pass-through in the British Wholesale Electricity Market

4.1 Introduction

Similar to most European wholesale electricity markets,[1] Great Britain (GB) has a small number of firms providing most of the country's electricity generation (EC [54]). In 2018, the six largest British electricity generation companies provided nearly 70% of all electricity generated nationally,[2] leading to concerns of market power, or a lack of market competition at the wholesale level. Retailers buy electricity from the wholesale market and then resell it to consumers. Wholesale costs, which are costs incurred to generate and sell wholesale electricity, are the greatest component of electricity bills in GB, consisting of about a third of a typical electricity bill (Ofgem [117]). Competition in the wholesale market promotes lower electricity bills for consumers, while market power tends to make electricity more expensive (Green and Newbery [73]).

Policymakers often rely on cost Pass-Through Rates (PTRs) to measure market competition since these can measure the degree to which a change in costs determines a change in prices (Ofgem [115], CMA [42]).[3] An increase in the input cost raises the marginal cost of electricity generation, but generators may absorb some of the increase by marking up their offer by a smaller or larger amount if the market is imperfectly competitive, depending on the shape of the residual demand (i.e. total demand minus renewables) curve. The PTR would

[1] The wholesale market for electricity is one where generators sell their electricity to retail companies. The latter then sell the electricity to homeowners and businesses in the retail market.

[2] See Ofgem.

[3] An alternative could be to estimate the pass-through elasticity, which informs about the percentage increase in prices arising from a 1% increase in cost.

then differ from 100%. However, given that consumers are inelastic to wholesale electricity prices in the short-run (Clò et al. [40]), a PTR significantly different from 100% would cast doubt on the assumption of competitiveness (CMA [42]).

Political events and reforms in the United Kingdom (UK) and the European Union (EU) could strongly influence the cost of energy to producers and hence to consumers. First, the UK voted to leave the EU in 2016, leading to widespread political and economic uncertainty and a substantially weaker Sterling. With half of the domestically-consumed natural gas imported from the Continent, and gas setting the British electricity price most of the time (Ofgem [115]), the cost of energy to British consumers is exposed to exchange rate fluctuations. Second, as EU carbon emissions Allowance prices (EUA prices, or the price of CO_2 set in the Emissions Trading System, ETS) have been too low to deliver the desired levels of emission reductions, the European Commission reformed the ETS by creating a Market Stability Reserve (MSR). The MSR came into effect in January 2019 and intends to cancel surplus allowances, tighten the carbon market and increase the EUA price (EC [54]). Higher carbon prices encourage cleaner electricity generation across Europe. From Figure 4.1, since late 2017 the anticipation of the reform's start has already driven an EUA price rally. Therefore, the Brexit referendum and introduction of the MSR resulted in substantial changes in Sterling exchange rates and carbon prices (respectively), providing an ideal test-bed for studying PTRs.

Unlike most empirical papers, which focus on carbon cost pass-through, our paper investigates a wide range of costs pass-through. In particular, we focus on fuel prices, carbon prices, and exchange rates PTRs, and whether they are consistent with the notion of a competitive British wholesale electricity market. Our investigation is conducted both theoretically and empirically.

We employ a sector-level[4] dataset and use econometrics to estimate long-run relationships between the input cost of electricity generation and the GB wholesale electricity price during 2015-2018. In the theoretical part, we show that the long-run relationship cannot be directly used as PTR. Instead, certain transformations are needed to deliver the estimates of PTRs. For example, we show that the carbon price PTR is equal to the ratio between the impact of carbon prices on electricity prices and the Marginal Emissions Factor (MEF) of the electricity system. Another example is that the fuel price PTR is equal to the ratio between the impact of fuel prices on electricity prices and the marginal share of the fuel.

We do not reject the null that gas prices, carbon prices, and exchange rates have been entirely passed through to the British wholesale electricity prices. We find heterogeneous

[4]Most related empirical literature uses thermal unit-level data to directly estimate the PTR (Fabra and Reguant [56], Sijm et al. [140]), while we show how to use a much cruder sector-level dataset to estimate the cost pass-through in a wholesale electricity market.

PTRs for different times of the day and days of the week, in agreement with the argument that this occurs due to electricity generators exercising different bidding strategies over different periods of the day (e.g. Jouvet and Solier [86], Fabra and Reguant [56]). We extend this argument by discussing generators' actual bidding strategy: the off-peak bids are mainly based on fuel costs, while the peak bids depend on both fuel and carbon costs. One reason is that fuel costs (especially gas prices) account for about 70% of the total cost of electricity generated from thermal plants. Another reason is that electricity generators purchase coal and gas via long-term forward contracts hence spot prices are not representative for the actual cost of fuels. Finally, assuming that the wholesale cost has been fully passed through to the domestic electricity bill,[5] we estimate that the depreciation of GBP caused by the Brexit referendum and MSR have raised British electricity bills for an average household by 6.7% in total.

The rest of the paper is structured as follows. Section 4.1.1 briefly describes how the wholesale electricity market works, Sections 4.1.3 and 4.1.2 provide background information regarding the Brexit referendum and ETS reform. Section 4.2 provides a review of related literature. Section 4.3 builds up the theoretical foundation for cost pass-through in the wholesale electricity market. Section 4.4 details the empirical methodology, Section 4.5 reports our results, and Section 4.6 discusses policy implications. Conclusions are drawn in Section 4.7.

4.1.1 The GB wholesale electricity markets

In Great Britain, wholesale electricity trading can take place bilaterally or via exchanges. However, by far the majority of electricity is traded through contracts covering timescales (markets) ranging from several years ahead to close to real-time. Among those markets, the day-ahead market has proven its efficiency, delivering a trusted market which sets bidding zone prices for the next 24 hours.

In the day-ahead market, at the supply side generators submit their hourly bids for a specified quantity of electricity that they are willing to supply. For each hour, bids from electricity generators are then arranged into a merit order from the cheapest to the most expensive, constructing the electricity supply curve. On the demand side, electricity retailers submit hourly prices they are willing to pay for specific demand one day in advance, and their offers are arranged from the highest price to the lowest, formulating the demand curve. For each hour, the intersection of the supply and demand curves determines the day-ahead

[5] This is a standard simplifying assumption to assess the PTR of wholesale costs into electricity prices. Another reason for this assumption is that most suppliers in GB are also generators, which makes it likely for the PTR to be at or close to 100%.

price. As demand increases, more expensive generation units are dispatched, resulting in higher electricity prices.

Generators' bidding functions are usually determined by the marginal cost of electricity generation, which are mainly given by the underlying fuel prices (coal or natural gas) and the carbon emissions cost. The GB carbon-intensive generators are subject to an additional carbon price relative to other European countries – in addition to the EU-wide carbon price (EU ETS), they also pay a GB-only carbon tax known as the Carbon Price Support (CPS). On the other hand, the exchange rate (particularly between Sterling and Euro) plays a crucial role in setting electricity prices, because GB is importing about a half of the natural gas consumption from the Continent and the trading currency with its continental neighbours is Euro.

Under the merit order theory of electricity supply, the electricity price is set by the dispatched power plants with the highest marginal cost. However, during 2015-2017 in GB, despite that the marginal cost for coal plants is higher than that for Combined Cycle Gas Turbines (CCGTs), CCGTs are directly[6] responding to about 60% of marginal demand changes, and about 70% of wind changes (see Chapter 2). In other words, CCGTs are the marginal fuel for GB during the period, thanks to their much higher flexibility of operation (than coal plants). Similar results are reported in Castagneto Gissey et al. [31], who found natural gas was the marginal fuel 65% of the hours in 2017. Given this, natural gas is potentially the fuel type that sets the day-ahead electricity price most of the time.

4.1.2 The ETS reform

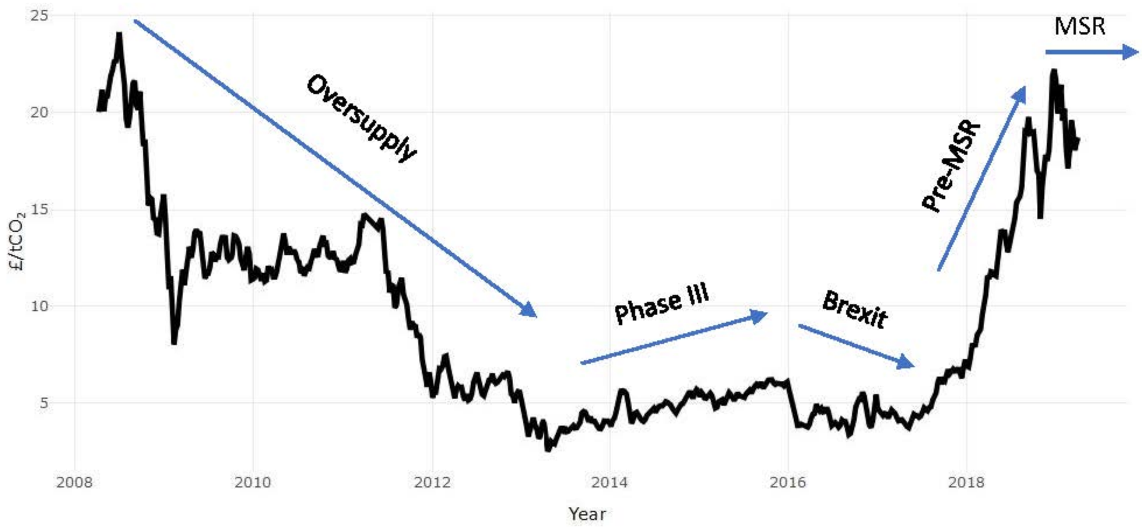
The EU Emissions Trading System (ETS) was launched in 2005 as the EU's main instrument to reduce its greenhouse gas (GHG) emissions from energy-intensive sectors. The EU ETS works on the "cap and trade" principle: a cap is set by the EU to limit the total amount of GHG that to be emitted, and companies can trade individual emission allowances (EU Allowances or EUAs, the tradable emission units under the ETS) with one another. Participants in the EU ETS can also buy international credits from global emission-saving projects external to the ETS. The cap is reduced over time so that the total emission falls. Companies must surrender a sufficient number of allowances to cover all of their emissions, or they face hefty fines.

If the carbon price is sufficiently high, it should discourage carbon-intensive generation and promote clean energy investment. As shown in Figure 4.1, the price peaked at almost £24/tCO_2 in 2008, while the freely allocated permits led to a large surplus of low-priced permits and a gradually crashing EUA price. The 2008 economic crisis and the inflow

[6] Indirectly, the numbers should be higher as imports and pumped storage may also come from CCGT plants.

of carbon credits from outside the EU further decreased the ETS price, which was then remained low during 2011-2017, providing wrong signals on carbon savings and low-carbon investments. In order to meet the EU's target of 40% GHG emission reduction by 2030 (relative to the 1990 level), reforming the ETS becomes a necessity.

Fig. 4.1 EU ETS carbon price, 2012-2018



Source: Weekly averaged EUA prices from Sandbag at sandbag.org.uk/carbon-price-viewer/.

Major reforms took effect since 2013 when the EU ETS entered Phase III. The most significant changes were the introduction of an EU-wide cap (instead of some country-wide caps)[7] on emissions and a progressive shift towards auctioning of allowances instead of the initial free allocation scheme. Phase III resulted in some gradual inclines in the EUA prices until 2016 when the market again experienced a drastic decline, followed by the Brexit referendum.[8] However, it is worth mentioning that the downward arrow around 2016 does not entirely attribute to Brexit – other factors such as changes in the relative fuel price may also interact with the carbon price.[9]

[7]The old country-wide cap is considered to be time-consuming, complex and not sufficiently transparent or harmonised.

[8]Facing the risks of a no-deal Brexit, the UK operators and traders with EUAs in their account may eventually lose the registry access. As a result, UK operators were motivated to sell/transfer their allowances, resulting in a surplus in the EUA supply and a reduction in the EUA price.

[9]Since 2016, coal has become the more expensive fuel than gas in electricity generation. The gas supplying the base load for major EU countries would potentially lower the demand of EUAs.

In 2014, the EC proposed a Market Stability Reserve (MSR) for the EU ETS, which was then implemented in January 2019. The aim was to correct the large surplus of allowances and make the electricity system more resilient to imbalances between the EUA supply and demand. It also aims to increase the carbon price and provide a working signal on the externality cost of CO_2 emissions. In February 2018, the EU Council approved the reform of the EU ETS for the period after 2020, which includes increasing the pace of emissions cuts,[10] doubling the number of allowances to be placed in the MSR between 2019-2023,[11] and building a new mechanism to limit the validity of allowances in reserve from 2023 onwards. As Figure 4.1 shows, the public anticipation of the start of the MSR has made carbon-intensive sectors stock more EUAs, tripling the EUA price from £8/tCO_2 in January 2018 to £25/tCO_2 in December 2018.

The consistently low EUA price since 2011 did not generate the required low carbon investments, leading the UK government to introduce the Carbon Price Support (CPS) in 2013. CPS is a GB-only[12] carbon tax that tops up the ETS price, levied on domestic power generators which is not replicated by other European countries. The CPS has been fixed at £18.08/tCO_2 since April 2015 until the fiscal year 2020-2021. [13]

4.1.3 The Brexit referendum

In a referendum held in June 2016, the UK has voted to withdraw from the EU and has formally abandoned the bloc on 31 January 2020. It entered a new phase called the Implementation Period that is expected to end on 31 December 2020. During the Implementation Period, the UK and all relevant parties in the energy sector are still bound by the EU law, meaning that the GB electricity generators would keep paying the EU carbon tax until 2021.

An instantaneous effect of voting to leave the EU was the drastic decline in the GBP/EUR exchange rate, shown in Figure 4.2. The steep depreciation resulted from expectations of capital outflows, a depressed investment outlook, and severe political instability.

The drastic decline in the value of Sterling could strongly affect the UK economy. The Bank of England (2018) estimated that a 5% depreciation adds almost 1% to the price of consumer goods. Forbes et al. [65] studied the implications of the Brexit vote, finding that

[10] The overall number of emission allowances will decline at an annual rate of 2.2% from 2021 onwards, compared with 1.74% currently.

[11] Between the first five years of its operation (2019-2023), the MSR will hold back 24% of the allowances in circulation, doubled from its regular feeding rate of 12%, which will be restored as of 2024.

[12] Northern Ireland belongs to the Irish Single Electricity Market with the Republic of Ireland. The Irish government declined to replicate the CPS, making it a GB-only carbon tax.

[13] The UK government is considering long term options for carbon pricing following Brexit. The most widely-discussed option is to introduce a Carbon Emissions Tax (CET) to replace the ETS share of total £/tCO_2 carbon prices. The CET could either be a fixed rate or completely follow the EUA price.

Fig. 4.2 GBP/EUA historical exchange rate, 2015-2018. The vertical dotted line indicates the EU withdrawal referendum date.

Source: Investing.com

the exchange rate PTR is relatively large in response to domestic monetary policy shocks but relatively small in response to domestic demand shocks. Their work helps explain why PTRs vary over time, such as why Sterling's post-crisis depreciation led to a sharper increase in prices than expected, and why Sterling's recent appreciations have had some more muted effects. Voting to leave also resulted in high inflations after 2017, which has cost an extra of £404 a year on an average British household (Breinlich et al. [24]). The UK stock market index (FTSE100) fell by about 4%, with companies most exposed to the UK and EU markets suffering the most significant share price falls (Davies and Studnicka [48]). As for the energy sector, the falling exchange rate is expected to have profound consequences throughout the energy value chain, with impacts on upstream oil and gas production and downstream generation and distribution (PwC [126]).

In the near future, leaving the EU could trigger regulatory changes that could significantly affect how the British energy system works. Those impact, both positive and negative, including but not limited to: leaving the EU ETS and replacing the EUA with a domestic Carbon Emissions Tax (CET), uncoupling interconnectors from the day-ahead cross-border electricity trading,[14] and changing the role of interconnectors in capacity auctions.[15] As a result, the UK's energy cost may be substantially affected. To estimate those impact, *ex-ante* simulation techniques such as a dispatch model instead of econometrics are preferable, and we leave them to future research.

4.2 Literature Review

Most studies calculating PTRs focused on the EUA cost pass-through to electricity prices in the context of the EU ETS. An early work done by Sijm et al. [140] find that the CO_2 cost PTR varies between 60% and 100% for German and Dutch wholesale electricity markets, though at the time, most of the emission allowances are freely allocated. As an extension of Sijm et al. [140], Zachmann and von Hirschhausen [163] find that the PTR is higher when the CO_2 price is rising than falling. Castagneto Gissey [29] uses the year-ahead data for four European countries during 2008-2012, to show that the PTRs ranged between 88% and 137%, with GB among the most cost-reflective in a sample of European markets. In contrary, Jouvet and Solier [86], in using different data and methodology, find that the estimated PTRs are insignificantly different from zero for most of the EU countries studied, especially during the second phase of the EU ETS.

The structure of electricity systems can be different for different countries, resulting in heterogeneous EUA cost pass-through. Honkatukia et al. [83] find a PTR of 75-95% in Finland during Phase I. Hintermann [77] finds it to be 81-111% in Germany during Phases I and II. Bariss et al. [12], in studying the Phase I and II, find that a €1/MWh increase in the ETS price was associated with an increase in the Nordic and Baltic electricity prices by €0.55/MWh and €0.67/MWh, respectively. Finally, Bunn and Fezzi [26] study the UK during Phase I, finding that a 1% shock in carbon prices translates on average into a 0.42% shock in UK electricity prices.

Many studies also found higher cost pass-through is associated with high demand and the utilisation rate of generation capacity (Sijm et al. [140], Honkatukia et al. [83], Jouvet and Solier [86], Fabra and Reguant [56]). This is because it is costly for fossil generators to

[14]From 4 February 2014, GB is coupled with France and the Netherlands. Market coupling ensures that the lower-price market would always import from the higher-price market day-ahead. Due to the different time zones, uncoupling means that traders have to anticipate the GB price when bidding for the cross-border trading for the next day, resulting in uneconomical trading.

[15]Capacity Markets usually take the form of forward contracts that last between one and three years, and are determined through an auction mechanism. Under the current scheme, generators are offered financial incentives to ensure that power plants are ready to provide emergency back-up when needed. The first British Capacity Auction (T-4) for delivery in 2018 was concluded on 18 December 2014 at a clearing price of £19.40/kW/year. However, On 15 November 2018, the EU's General Court issued a judgement annulment, depriving the capacity payment that the GB capacity market participants expected to receive.

shut down and then start up again, hence generators are more likely to bid a lower price (than the marginal costs) during off-peak hours in order to maximise overall profit. On the other hand, the utilisation rate of generation capacity is high during peak periods, indicating that fossil-fuelled generators are able to exercise market power, in which case they will bid higher than its marginal costs when supplying at peak. We will extent this argument by revelling generators exact bidding strategies during peak and off-peak periods.

The cost pass-through for other forms of carbon taxes can also be found in the literature. Examples include studies investigating the Australian Emissions Trading Scheme (Nazifi [101], Maryniak et al. [97]), the British Carbon Price Support (see Chapter 3), and California's CO_2 cap-and-trade programme (Woo et al. [158]).

Several studies consider markets for other pollutants. For example, Kolstad and Wolak [93] consider how firms used NO_x prices to exercise market power in the electricity market of California, finding evidence that firms respond differently to environmental cost shocks relative to shocks in other marginal costs. Fowlie et al. [67] study firms' responses in the NO_x Budget Program, finding that the degree of emission cost internalisation depends on the degree to which the production was subsidised.

Fuel price PTRs are usually the by-products from studies on carbon price pass-through, especially in literature during the past decade. Hintermann [77] finds that fuel prices are passed through to electricity prices more evenly than carbon prices in Germany. A similar result is also reported by Fabra and Reguant [56], who argue that Spanish firms do not pass on fuel prices to the same degree as allowance costs. They consider that a reason for this is the presence of transaction costs and long-term contracts for fuels and conclude that spot prices do not perfectly represent firms' opportunity costs related to fuel use.

Castagneto Gissey [29] finds that the British coal- and gas-price PTRs in 2007-2012 were 90% and 112%, respectively, with PTRs the largest for the fuel type that was more often used for generation. Ahamada and Kirat [3] study France and Germany during ETS Phase II, finding that coal-fired units are more often the price-setting marginal units, a factor which they find explains the higher PTR of coal prices. The CMA [42] studies pass-through of fuel prices to retail electricity prices. The study has substantial competition policy implications for the UK retail electricity sector which was shown to exhibit market power.

Finally, literature regarding the impact of exchange rates on wholesale electricity prices is surprisingly limited. The Ontario Energy OEB [111] emphasises that the exchange rate influences Canadian electricity prices by affecting the fuel price and the electricity price from the neighbouring US market. Castagneto Gissey and Green [30] study a sample of European electricity markets during the 2008 financial crisis and find that the exchange rate affected electricity prices in their volatility but did not have a significant effect in their levels. A more recent study finds that in the long-run, electricity prices would increase by 0.56% following a 1% increase in the real exchange rate in Ghana (Adom et al. [1]).

4.3 Competition and Market Power

The fundamental measure of market power is the price-cost margin, which is the degree to which prices exceed marginal costs (Borenstein et al. [19]). However, measuring price-cost margins is difficult for the electricity industry because costs are usually private information for the producers.

The most common measures of market power are market shares and market concentration. Market shares inform us about the size of a company relative the rest of the market, while market concentration indicates the extent to which a market is dominated by only a few firms. However, it is not always the case that market shares and market concentration can fully explain market power, as many other factors can affect the degree of competition within an industry, such as the incentive of producers and the price elasticity of demand (Borenstein et al. [19]).

Pivotality analysis is also widely adopted (Ofgem [113]). It examines whether at least 1 megawatt (MW) of the company's generation is required by the system to meet demand. The lack of competition for that additional MW of supply would allow the firm to exercise its market power by increasing electricity prices more than it otherwise would. However, models falling in this category consider the impact of individual firms, hence require data with much higher resolution, most of which are not publicly available.

Our work focuses on a wide range of cost PTRs, which inform the welfare implications of various types of price discriminations and imperfect competition (Fabra and Reguant [56], Pless and van Benthem [125]). In this Section, we first build a simple game theory model to derive the relationship between PTR and market competition, under the assumption of Cournot competition. Then, we separately look at fuel prices, carbon prices, and exchange rate PTRs.

4.3.1 Cost Pass-through: an economic theory

The wholesale electricity market is typically seen as consistent with Cournot competition (see e.g. Lundin and Tangerås [94], Gal et al. [69], Dressler [53], Willems [156], Willems et al. [157], Andersson and Bergman [7]), a subtype of oligopolistic competition where generators compete on the amount of output they will produce, as opposed to the price they will set.

Suppose the GB electricity supply side of a set of $N = \{1, 2, ..., n\}$ firms. As the wholesale price is set by marginal fuels, N should only consist of power plants that can activity set the wholesale price, including coal and CCGT plants, imports, pumped storage, and hydro plants.[16] We assume that for each fuel type, the number of firm is determined by its marginal share,[17] therefore each firm's capacity to respond to the marginal demand change is the same. For example, in Appendix C.1 we find the marginal share for CCGTs is 60%, then the number of CCGTs in the market is $0.6N$. Suppose all firms face a common inverse demand curve $p(Q)$, where Q denotes the total output. $p(Q)$ is assumed to be negatively related to Q, hence $p'(Q) < 0$. Firm $i \in N$ chooses how much output q_i to sell to the market to maximise its profit $\phi(q_i)$:

$$\max_{q_i} \quad \phi(q_i) = q_i \cdot p(q_i + Q_{-i}) - c_i(q_i) - t_i \cdot q_i, \tag{4.1}$$

where the first term, $q_i \cdot p(q_i + Q_{-i})$, denotes the revenue for firm i from selling quantity q_i. Q_{-i} denotes the amount of output from all other firms and is taken as given, therefore $Q_{-i} = Q - q_i$. $c_i(q_i)$ is the cost function for firm i. Finally, t_i is a cost shifter for firm i. For example, t_i could be the EUA price on each unit of electricity generated from the firm.

Taking the first order condition of (4.1), firm i sets $q_i = q_i^*$ to satisfy

$$q_i^* \cdot p'(q_i^* + Q_{-i}) + p(q_i^* + Q_{-i}) - c_i'(q_i^*) - t_i = 0. \tag{4.2}$$

Aggregating across all firms gives

$$\sum_{i \in N} q_i^* \cdot p'(q_i^* + Q_{-i}^*) + \sum_{i \in N} p(q_i^* + Q_{-i}^*) - \sum_{i \in N} c_i'(q_i^*) - \sum_{i \in N} t_i = 0, \tag{4.3}$$

where Q_{-i}^* denotes the optimal output from all other firms. Under market equilibrium, $q_i^* + Q_{-i}^* = Q^*$, where Q^* denotes the equilibrium total output. Then a simplified version of (4.3) can be expressed as

$$Q^* \cdot p'(Q^*) + n \cdot p(Q^*) - \sum_{i \in N} c_i'(q_i^*) - \sum_{i \in N} t_i = 0, \tag{4.4}$$

where $p(Q^*) = p^*$ denotes the equilibrium price.

[16] As nuclear and renewable power plants enjoy a close-to-zero marginal cost, they are regarded as base load — (almost) always producing at their maximum available output. Therefore, it is commonly agreed that nuclear and renewable power plants are not capable of setting wholesale prices through actively changing their productivity. Other fuels such as oil and Open Cycle Gas Turbines (OCGTs) barely operate, hence negligible.

[17] The proportion of the fuel type that respond to demand changes that margin. In Appendix C.1, we show how marginal shares are empirically determined.

Applying the implicit function theorem on (4.4) and differentiating with respect to $\bar{t} = 1/n\sum_{i\in N} t_i$, the average cost shifter across the whole industry, and assuming the cost function $c_i(q_i)$ to be linear with q_i, such that $c''(q_i^*) = 0$, we have

$$(n+1)\cdot p'(Q^*)\cdot \frac{dQ^*}{d\bar{t}} + Q^*\cdot p''(Q^*)\cdot \frac{dQ^*}{d\bar{t}} - n = 0. \tag{4.5}$$

Rearranging, we obtain $dQ^*/d\bar{t}$, the change in the equilibrium total output following a change in the average cost shifter, as

$$\frac{dQ^*}{d\bar{t}} = \frac{n}{(n+1)\cdot p'(Q^*) + Q^*\cdot p''(Q^*)} \tag{4.6}$$

Knowing that the equilibrium price $p^* = p(Q^*)$ is a function of the equilibrium total output Q^* hence $dp^*/dQ^* = p'(Q^*)$, we can derive the rate of cost pass-through for the industry under Cournot competition as

$$\begin{aligned}\frac{dp^*}{d\bar{t}} =& p'(Q^*)\cdot\frac{dQ^*}{d\bar{t}}\\ =& \frac{n\cdot p'(Q^*)}{(n+1)\cdot p' + Q^*\cdot p''(Q^*)}\\ =& \frac{n}{(n+1) + Q^*\cdot p''(Q^*)/p'(Q^*)}.\end{aligned}$$

Letting $\xi = -Q^*\cdot p''(Q^*)/p'(Q^*)$ and rearranging we have

$$\xi = -\frac{Q^*}{p'(Q^*)}\cdot\frac{\partial p'(Q^*)}{\partial Q^*},$$

meaning that ξ is the *elasticity of slope* of inverse demand, then the PTR is

$$\frac{dp^*}{d\bar{t}} = \frac{n}{(n+1)-\xi}. \tag{4.7}$$

When $n = 1$, the PTR under Cournot competition becomes the case of monopoly. When n is large, the Cournot case converges to the perfect competition result. As the *slope of* electricity demand curve is usually considered to be inelastic to the total output, and sometimes even to be locally inelastic (i.e. a locally linear demand curve), ξ is small and the PTR would mainly depend on the number of firms in the industry, which converges to 100% as n becomes large.

Other forms of expressions of PTR can be found in Bulow and Pfleiderer [25], Seade [136] and more recently Weyl and Fabinger [153] and Reguant [128], though their models might be based on different market structures.

4.3.2 Cost pass-through in wholesale electricity markets

As the paper examines the cost pass-through of coal and gas price, the carbon price, and the exchange rate to the GB wholesale electricity price. Depending on which exact PTR we are investigating, the interpretation on the average cost shifter $\bar{t}$ in 4.7 can be different.

The EUA pass-through

Suppose t_i in (4.1) represents the carbon price from EUA for firm i. Then, the EUA cost for coal plants would be $t_{\mathrm{COAL}} = EF_{\mathrm{COAL}} \cdot p^{\mathrm{EUA}}$, and for CCGT plants would be $t_{\mathrm{CCGT}} = EF_{\mathrm{CCGT}} \cdot p^{\mathrm{EUA}}$, where EF denotes emission factors for different fuel types and p^{EUA} denotes the EUA price in £/t$\mathrm{CO_2}$. Because hydro plants emit zero $\mathrm{CO_2}$, then $t_{\mathrm{HYD}} = EF_{\mathrm{HYD}} \cdot p^{\mathrm{EUA}} = 0$. The emission factor for pumped storages depends on which fuel types is supplying at margin when pumping/charging. For GB, it is mostly likely to be CCGTs and/or coal-fired power plants. We denote the emission factor for pumped storage as EF_{PS}, then $t_{\mathrm{PS}} = EF_{\mathrm{PS}} \cdot p^{\mathrm{EUA}}$.

In addition to domestic fossil plants and pumped storages, any changes in electricity demand can also be met by imports, through trading in cross-border electricity interconnectors. The EUA cost for the imported electricity would be $t_{\mathrm{K}} = MEF_{\mathrm{K}} \cdot p^{\mathrm{EUA}}$, where $\mathrm{K} \in \{\mathrm{FR}, \mathrm{NL}, \mathrm{IR}\}$ representing imports from France, the Netherlands, and the island of Ireland,
footnoteGB is also connected with Belgium since 31 January 2019, which is not within the period of studying. where MEF_{K} denotes the Marginal Emission Factor (MEF) for country K.[18] Then,

$$\bar{t}^{\mathrm{EUA}} = \frac{1}{n_1 + n_2} \left(\sum_{i_1 \in N_1} EF_{i_1} \cdot p^{\mathrm{EUA}} + \sum_{i_2 \in N_2} MEF_{i_2} \cdot p^{\mathrm{EUA}} \right),$$

where $N_1 = \{1, \ldots, n_1\}$ consists of coal, gas, hydro, and pumped storage firms, $N_2 = \{n_1 + 1, \ldots, n_1 + n_2\}$ consists of firms biding for cross-border electricity trading. The values of EF_{i_1} has to be within the set of $\{EF_{\mathrm{COAL}}, EF_{\mathrm{CCGT}}, EF_{\mathrm{HYD}}, EF_{\mathrm{PS}}\}$, and the values of MEF_{i_2} has to be within the set of $\{MEF_{\mathrm{FR}}, MEF_{\mathrm{NL}}, MEF_{\mathrm{IR}}\}$.

[18] Despite that electricity imported from the European Continent and the Island of Ireland may come from some particular power plants, the British System Operator imports at the foreign wholesale prices, which is set by the foreign marginal plants.

By definition, $N = N_1 \cup N_2$, $\emptyset = N_1 \cap N_2$, and $n = n_1 + n_2$. A full PTR of the EUA cost requires the marginal effect of the EUA price on the wholesale price to be close to $\bar{t}^{\mathrm{EUA}}$, which is also known as the MEF for GB.

Fuel prices pass-through

Now suppose the gas price for a particular short period is $p^{\mathrm{CCGT}} = \bar{p}^{\mathrm{CCGT}} + p_{\varepsilon}^{\mathrm{CCGT}}$, where $\bar{p}^{\mathrm{CCGT}}$ denotes the average gas price during the whole period of studying and $p_{\varepsilon}^{\mathrm{CCGT}}$ denotes the price that deviates from its average. Any changes in the gas price is due to changes in $p_{\varepsilon}^{\mathrm{CCGT}}$.

For simplicity, we assume that all other input costs, except p^{CCGT}, are held constant, and that the cost function for a CCGT firm is $c_{\mathrm{CCGT}}(q_{\mathrm{CCGT}}) = \bar{p}^{\mathrm{CCGT}} \cdot q_{\mathrm{CCGT}} + C$, where C represents a fixed cost such as the wear and tear on the machine. In this case, t_i in (4.1) can be interpreted as the gas-price shifter $p_{\varepsilon}^{\mathrm{CCGT}}$.

Note that any changes in $p_{\varepsilon}^{\mathrm{CCGT}}$ will have influence not only on CCGTs, but also on imports and pumped storages, which may also get supplied by (foreign or domestic) CCGTs. Then

$$\bar{t}^{\mathrm{CCGT}} = s^{\mathrm{CCGT}} \cdot p_{\varepsilon}^{\mathrm{CCGT}},$$

where s^{CCGT} is the marginal share of CCGTs *plus* the marginal share of imports and pumped storages that comes from CCGTs. A full PTR of the gas price requires the marginal effect of gas price on the wholesale price to be close to s^{CCGT}.

Applying the same logic to the case of coal, $\bar{t}^{\mathrm{EUA}}$ can be expressed as

$$\bar{t}^{\mathrm{COAL}} = s^{\mathrm{COAL}} \cdot p_{\varepsilon}^{\mathrm{COAL}},$$

where s^{COAL} is a mirror image of s^{CCGT}, and a full PTR of the coal price requires the marginal effect of coal price on the wholesale price to be close to s^{COAL}.

The exchange rate pass-through

The impact of the exchange rate on the wholesale electricity price may not be reflected in the Cournot competition model. Although the exchange rate would affect both fuel and carbon prices, the empirical analysis in Section 4.5 estimates the effect of exchange rate on the wholesale price accounting in its impacts on the fuel and carbon prices, whose values are taken in Sterling. Under the scenario of a full PTR, a 1% depreciation in Sterling relative to Euro would result in a 1% increase in the GB wholesale price.

4.4 Econometric Methods

We use econometrics to study how would the GB day-ahead wholesale electricity price react when there are changes in the input costs of electricity generation during the period of 2015-2018. We begin by introducing the data used in this study and proceed by covering the underlying model and related technical considerations.

4.4.1 Data

All data ranges from 1st April 2015[19] to 31st December 2018,[20] and hourly data is averaged to daily means. The hourly GB day-ahead electricity price (i.e. the spot market price, in Sterling) is collected from the Entso-e Transparency Platform. The daily National Balancing Point gas price (in Sterling) comes from the InterContinental Exchange and is converted from £p/therm to £/MWh_e (i.e. Pounds per Megawatt hour of electricity, used interchangeably with MWh in this chapter) assuming a Lower Heating Value efficiency for CCGTs of 54.5%.[21] The daily coal price, from CME Globex in \$ /short ton, is converted to £/MWh_e, using the daily GBP/USD exchange rate, assuming an average thermal efficiency for the GB coal-fired power plants of 35.6%.[22] Note that coal prices in the US can be different from that consumed by GB generators, mainly because of transportation costs. Therefore, we adjust the US daily coal price data based on the UK quarterly coal price data from the Department for Business,

[19] The British Carbon Price Support (CPS) was raised from £9.55/tCO_2 to £18.08/tCO_2 on 1st April 2015 and has been stabilised since then. This may influence GB electricity prices. In the empirical part, we start our analysis from 1st April 2015, such that the CPS is fixed during the period of study, and is excluded from our regression analysis.

[20] Our analysis does not cover 2019 because during the entire year, the GB electricity generators are uncertain about the carbon prices they will pay for electricity generation. During the first half of 2019, expectations of the date the UK would leave the EU changed from March to November (and then further delayed), with or without a deal. If the UK leaves the EU with a suitable deal, the expectation was that GB electricity generators paying both EUA and the £18 CPS before November 2019, and pays the £16 Carbon Emission Tax (CET) plus the £18 CPS from November 2019. Under the no-deal scenario, for the period January 2019 to October 2019, electricity generation will incur only the £18 CPS, with no EUA or CET; For the period November 2019 to December 2019, electricity generation will incur £16 CET plus £18 CPS; From January 2020, electricity will incur CET at the 2020 rate (which may still be £16 or may be set at another level in the next Budget) plus £18 CPS. As UK formally left the EU on 31st January 2020, the actual carbon tax that GB electricity generators would pay EUA plus CPS until the end of 2020.

[21] 1 (UK) therm is equivalent to 29.31 kWh_{th}. Under the Lower Heating Value efficiency of 54.5%, 1 (UK) therm is equivalent to 15.97(=29.31×54.5%) kWh_e.

[22] Thermal efficiencies for coal and CCGT plants are taken from Chapter 2.

Energy & Industrial Strategy (BEIS)[23] The daily EUA price is the EU ETS closing spot price and is converted from Euro to Sterling using the daily exchange rate.[24]

The day-ahead forecasts of GB renewable (wind and solar) generation and domestic demand come from the Entso-e Transparency Platform.[25] Besides, when nuclear generators are under maintenance or suffering from outages, fossil fuel needs to backup the deficit, which affects the wholesale price. Due to data unavailability, we use the actual daily nuclear generation as a proxy for the day-ahead forecast of nuclear generation.[26] Table 4.1 provides summary statistics for all variables involved in the preliminary regression analysis (Section 4.5.1).

Table 4.1 Summary Statistics, Day-ahead Markets

Variable	Abbr.	Unit	Obs.	Mean	S. D.	Min.	Max.
GB day-ahead Prices	P_t^{GB}	£/MWh	1371	46.24	10.98	28.12	170.15
Coal Prices	P_t^{COAL}	£/MWh$_e$	1371	24.16	5.80	13.34	33.69
Gas Prices	P_t^{GAS}	£/MWh$_e$	1371	34.06	7.50	20.29	54.46
EUA Prices	P_t^{EUA}	£/ tCO$_2$	1371	7.52	4.58	3.34	22.83
GBP/EUR XR	e_t	£/€	1371	1.21	0.10	1.08	1.44
GB Renew. Gen.	R_t^{GB}	GW	1371	6.10	2.76	1.03	14.94
GB Demand	D_t^{GB}	GW	1371	33.95	4.15	24.73	45.26
GB Nuclear Gen.	N_t^{GB}	GW	1371	7.34	0.67	4.69	8.83

Figure 4.3 shows the 28-day moving averages of the electricity, coal, gas, and EUA prices during the period of studying, with strong comovements between gas and electricity prices. The gap between gas and electricity prices are becoming wider mainly because the recent drastic increase in the EUA price.

4.4.2 Vector Error Correction Model

We implement the Vector Error Correction Model (VECM) to study the impact of fuel prices, carbon prices, and exchange rates on the British wholesale electricity price. The same model has been widely used in studying the cost pass-through in the energy market (see, e.g., Alexeeva-Talebi [5], Delft and Oeko-Institut [50], Freitas and Da Silva [68], Bunn and Fezzi

[23] See BEIS. We aggregate the daily data into quarterly, subtract from the BEIS data, and adjust the daily data by adding this quarterly averaged margin to each day.

[24] Note that the coal price, gas price, EUA price, and the exchange rate are only available for weekdays; hence, we use the most adjacent values as proxies for any missing data.

[25] The "generation forecast for wind and solar" and the "day-ahead forecast on total load".

[26] Nuclear power plants are highly inflexible and serve baseload power in GB, meaning that the actual nuclear generation can potentially be very close to its day-ahead forecast.

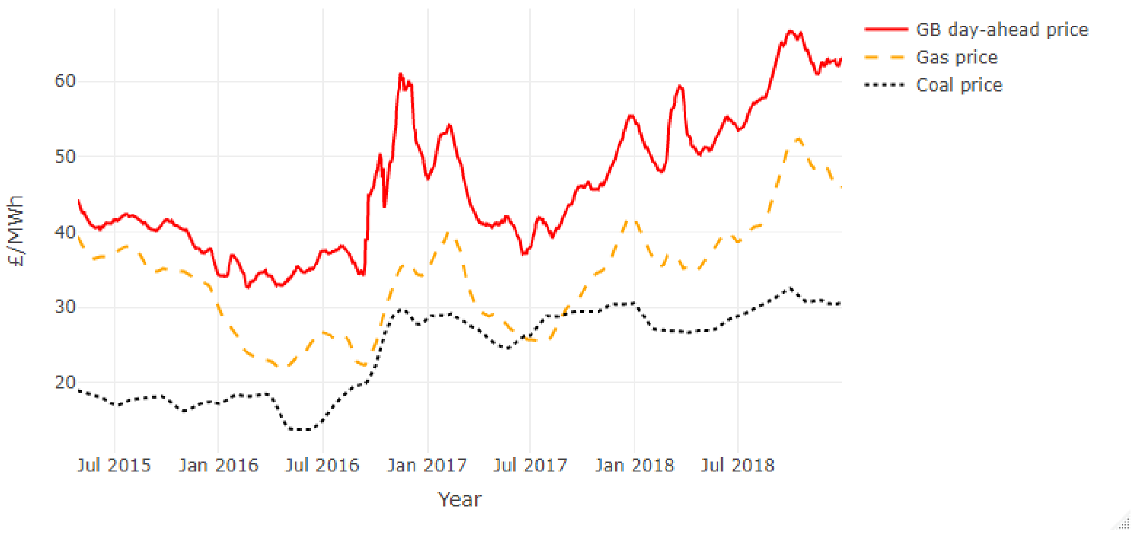


Fig. 4.3 Electricity, coal, and gas prices, April 2015 - December 2018

[26], Mohammadi [99], Fell et al. [62]), as it effectively captures both short-run and long-run relationships among variables of interest.

In addition, when estimating the impact of input costs on the wholesale electricity price, endogeneity can become an issue when interactions between fuel prices and wholesale prices play a critical role in the wholesale price formation (Knittel and Roberts [92]). This also applies to the relationship between wholesale prices and carbon prices, and between wholesale prices and exchange rates, suggesting that all variables representing the input cost for generating electricity have the potential to be endogenous. The VECM allows us to treat both wholesale electricity prices and input costs as endogenous.

The specification for the VECM can be expressed as:

$$\Delta \boldsymbol{y}_t = \boldsymbol{\alpha}(\boldsymbol{\beta}' \boldsymbol{y}_{t-1}) + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{y}_{t-i} + \boldsymbol{B} \boldsymbol{z}_t + \boldsymbol{C} \boldsymbol{d}_t + \boldsymbol{u}_t, \tag{4.8}$$

where t represents days, Δ is the first-different operator, and $\boldsymbol{y}_t$ is an $m \times 1$ vector of dependent variables. In the preliminary regression reported in Section 4.5.1, $\boldsymbol{y}_t$ includes the daily averaged GB day-ahead price (P_t^{GB}), coal and gas prices (P_t^{COAL} and P_t^{GAS}), EUA price (P_t^{EUA}), and GBP/EUR exchange rate (e_t).[27] All variables in $\boldsymbol{y}_t$ are $I(1)$ time series processes (i.e., time series with unit roots, tested in Appendix Table C.4) and are cointegrated (tested in Appendix Table C.6).

[27] An alternative would be using the GBP/USD exchange rate, but the result suggests that the GBP/USD exchange rate has insignificant impact on the GB electricity price.

$\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $m \times r$ matrices of full column ranks, and $\boldsymbol{\beta}'\boldsymbol{y}_{t-1} \sim I(0)$. $\boldsymbol{\beta}'\boldsymbol{y}_{t-1}$ is the $r \times 1$ vector of cointegration relations, known as the long-run (LR) relationships. $\boldsymbol{\alpha}$ is known as the vector of error correction (EC) coefficients, which represent the speed to convergence when the system deviates from its long-run equilibrium. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ can be identified by setting one of the parameters in $\boldsymbol{\beta}$ to 1. In our case, the coefficient for P_{t-1}^{GB} is set to 1. $\boldsymbol{\Gamma}_i$ consists of coefficients capturing the short-run (SR) relationships.

$\boldsymbol{z}_t$ is a vector of stationary, or $I(0)$ exogenous stochastic variables, including the day-ahead forecast of electricity demand (D_t^{GB}) and wind generation (W_t^{GB}), as well as nuclear generation (N_t^{GB}). $\boldsymbol{d}_t$ is a vector of deterministic variables containing a time-invariant constant term, a deterministic trend, and day-of-week and quarterly time dummies. $\boldsymbol{B}$ and $\boldsymbol{C}$ are coefficient matrices. Finally, $\boldsymbol{u}_t$ is an $m \times 1$ vector of unobserved error terms, and is assumed to be stochastically independent, or $\boldsymbol{u}_t \sim (\boldsymbol{0}, \boldsymbol{\Sigma}_u)$.

We implement the Akaike Information Criterion to determine the lag lengths (p) for dependent variables, and the optimal lag length is $p = 4$ (see Appendix Table C.5).

In equation (4.8), the input costs are treated as endogenous. However, one may argue that fuel and carbon prices are mainly determined by the European and world markets, while a single country like GB can have little influence on the fuel price. If this is the case, treating fuel prices as exogenous can improve estimation efficiency. This ambiguity on whether input costs should be treated as endogenous suggests to implement tests for (weak) exogeneity and to use the test results to formulate specifications for the VECM.

Exogeneity can be tested in a VECM specification as (4.8), with the null hypothesis being that the EC parameters (i.e., the second to fifth parameters of α) are jointly significantly different from zero. If we fail to reject the null, then the corresponding variables should be treated as weakly exogenous. The test shows that coal and gas prices, EUA prices, as well as exchange rates are weakly exogenous,[28] suggesting employing the structural VECM model (Pesaran [121]), with $\boldsymbol{y}_t = (\boldsymbol{y}_t^{\star\prime}, \boldsymbol{x}_t{}')'$, where $\boldsymbol{y}_t^{\star}$ with dimension $m_y \times 1$ consists of endogenous variables and $\boldsymbol{x}_t$ with dimension $m_x \times 1$ consists of weakly exogenous variables, and $m_y + m_x = m$.

4.5 Results

In this section, unless specified, "wholesale price" refers to the GB day-ahead wholesale electricity price. Section 4.5.1 analyses preliminary results estimating the impact of input costs of electricity generation on the wholesale price, as well as the corresponding PTRs. In Section 4.5.2, we vary the regression specification to conduct robustness checks, and split

[28] $\chi^2_{(3)} = 1.52$ with p-value 0.82.

the data by peak and off-peak (weekdays and weekends). We give intuition on why PTRs are heterogeneous with time.

4.5.1 Preliminary Results

Recall that the test for weak exogeneity suggests that we should treat coal and gas prices, EUA prices, and GBP/EUR exchange rates as weakly exogenous. By restricting the corresponding error correction (EC) parameters to zero, Table 4.2 reports the regression result for the structural VECM.

Table 4.2 VEC Model Results

Long-run Dynamics						
Const.	P_{t-1}^{GB}	Trend	P_{t-1}^{COAL}	P_{t-1}^{GAS}	P_{t-1}^{EUA}	e_{t-1}
-82.044	1.000	0.007	-0.075	-0.831***	-0.461**	53.314***
			(0.150)	(0.090)	(0.165)	(9.232)

Short-run Dynamics		Weakly Exogenous Variables			
	ΔP_t^{GB}	ΔP_t^{COAL}	ΔP_t^{GAS}	ΔP_t^{EUA}	Δe_t
EC_{t-1}	-0.553***	—	—	—	—
	(0.036)	—	—	—	—
Const.	-14.261***	0.210	-0.282	-0.180	-0.003
	(3.391)	(0.180)	(0.439)	(0.147)	(0.004)
Trend	0.003***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_t^{GB}	0.522***	-0.004	0.004	0.004	0.000
	(0.077)	(0.004)	(0.010)	(0.003)	(0.000)
R_t^{GB}	-0.597***	-0.004	-0.003	0.005	0.000
	(0.058)	(0.003)	(0.008)	(0.003)	(0.000)
N_t^{GB}	-0.449*	-0.007	0.014	0.000	0.000
	(0.227)	(0.012)	(0.029)	(0.010)	(0.000)

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

In Table 4.2, the estimated coefficients in the "Long-run Dynamics" panel are estimates for $\boldsymbol{\beta}$ in equation 4.8, which estimate the long-run relationships between electricity prices and input costs. In the long-run, a fall in the GBP/EUR exchange rate (e_t) by 1,000 basis point (i.e. a 0.1 reduction) is associated with an increase in the wholesale price by £5.33/MWh. Given the 2015-2018 average wholesale price is £46.23/MWh (in Table 4.1), under the null hypothesis of 100% exchange rate PTR, a 0.1 change in the GBP/EUR exchange rate is supposed to be associated with a £4.62/MWh($= 46.23 \times 0.1$) opposite change in the wholesale price. Since the estimated £5.33/MWh(s.e.=0.92) is not statistically significantly different from £4.62/MWh, we do not reject the null.

Our results also show that in the long-run, a £1/MWh$_e$ increase in the gas price (P_t^{GAS}) is associated with a £0.83/MWh$_e$ increase in the wholesale price. Based on our analysis in Section 4.3.2, a full pass-through of gas price would require the long-run relation to be statistically close to the marginal share of CCGTs, when the proportion of imports and pumped storage that comes from CCGTs are also taken into account. In Appendix C.1, we replicate Chapter 2 to estimate the marginal fuel of GB during the period of studying, and found that CCGTs respond to at least 60% of demand changes under the assumption that none of the supply from imports and pumped storage are from CCGTs. This number raises to 78% if we assume that the supply from imports and pumped storages are entirely from CCGTs. Given this, the 99% confidence interval for the gas price PTR to the wholesale price is [100%,177%] in the former case, and [77%,136%] the the latter case.[29] In other words, in any scenario, we fail to reject the null that the gas price PTR is statistically significantly different from 100% at 1% significant level. In fact, if at least 31% of the supply from imports and pumped storages comes from CCGTs (which is very likely), we would not reject the null at 5% significant level.[30]

The long-run relationship between coal (P_t^{COAL}) and wholesale prices is not significantly different from zero. Furthermore, the estimate suffers from a large standard error, probably because of low variation in coal prices during the past few years. As a result, the estimation is not informative, and we are unable to make a credible discussion about the PTR of coal.[31]

A £1/tCO_2 increase in the EUA price (P_t^{EUA}) corresponds to a £0.46/MWh increase in the wholesale electricity price. As discussed in Section 4.3.2, a 100% EUA price PTR requires that the estimated long-run relationship between the EUA price and the wholesale electricity price to be close to the Marginal Emission Factor (MEF) of the GB electricity supply.[32] From our replicated results in Appendix C.1, during the period of studying, the MEF for the

[29]For the former case, the confidence interval is calculated from $(0.83 \pm 2.58 \times 0.09)/0.60$, where 0.09 is the corresponding standard error and 2.58 is the critical value at 1% significant level. For the latter case, it is calculated from $(0.83 \pm 2.58 \times 0.09)/0.78$.

[30]From the regression results in Appendix C.1, about 18% of the marginal demand is answered by imports and pumped storages. 31% of the 18% means that there is an additional 5.5% of marginal demand is answered by CCGTs, making gas plants answering a total of 65.5% of marginal demand. In this case, 0.655 is the lower bound of the 95% confidence interval of the estimate 0.831(s.e.=0.090) in Table 4.2.

[31]However, the estimation result itself, as least, do not reject the null hypothesis that the coal price pass-through is 100%.

[32]Chapter 2 estimate both short-run and long-run MEFs. In this chapter, MEF always refers to the short-run MEF that measures the impact of (half-)hourly change in demand on CO_2 emissions.

GB electricity supply is between 0.429 and 0.525 tCO_2/MWh.[33] Either way, we fail to reject the null that the EUA price has a 100% PTR.

In the "Short-run Dynamics" panel, the coefficients of error correction (EC), EC_{t-1}, estimates $\boldsymbol{\alpha}$ in equation 4.8. The coefficients for the EC term estimate the speed of convergence to long-run equilibrium. Precisely, if the wholesale price diverges from the long-run equilibrium on the day t due to unexpected market shocks, then on the day $t+1$, about 55% of that disequilibrium is dissipated before the next time period, and 45% remains. If there is no further shock on the day $t+1$, then on the day $t+2$, about 55% of the remaining (45% of) disequilibrium would be adjusted and dissipated; and so forth.

Finally, the estimation result also suggests that the wholesale price is positively affected by electricity demand (D_t^{GB}) and negatively affected by renewable (R_t^{GB}) and nuclear (N_t^{GB}) supply.

4.5.2 Robustness Checks and Extensions

In section 4.5.2, we report robustness checks by varying regression specifications of the preliminary regression reported in Section 4.5.1. In Section 4.5.2-4.5.2, we extend the regression analysis by considering heterogeneous effects within days (peak and off-peak) and across days (weekdays and weekend). Finally, in Section 4.5.2 we explain the reason that the PTRs can be different for different time of the day and different days of the week.

Table 4.3 shows the regression results discussed in this subsection, with only the long-run dynamics and the EC terms reported.

Robustness checks

Regression (i) removes the weak exogeneity assumption in Section 4.5.1. The regression results are similar to those the preliminary case, reassuring the validity of treating input costs are weakly exogenous.

Regression (ii) takes the log of wholesale prices, coal and gas prices, and EUA prices, hence estimates the elasticities of the wholesale price relative to the input costs. The result shows that in the long-run, a 1% increase in the gas price is associated with a 0.6% increase in the wholesale price. Note that from Table 4.1, the average gas price is £34.06/MWh$_e$, and the average wholesale price is £46.24/MWh. Then, the regression result suggests that if the average gas price is increased by £0.34/MWh$_e$ (1% of the average), the wholesale price will raise by £0.28/MWh (0.6% of the average). Alternatively, the wholesale price would be

[33]This is calculated under two extreme cases where we assume that the supply from imports and pumped storages is either entirely from CCGTs, or entirely from coal-fired power plants.

Table 4.3 Robustness Check

	(i)	(ii)	(iii)		(iv)	
	ENDOG.	LOG	OFF-PEAK	PEAK	W.DAY	W.END
Long-run Dynamics						
P_{t-1}^{GB}	1.000	1.000				
$P_{t-1}^{\text{GB,OFF}}$			1.000			
$P_{t-1}^{\text{GB,PEAK}}$				1.000		
$P_{t-1}^{\text{GB,W.DAY}}$					1.000	
$P_{t-1}^{\text{GB,W.END}}$						1.000
P_{t-1}^{COAL}	-0.106	-0.040	0.202**	-0.214	-0.128	0.035
	(0.149)	(0.045)	(0.081)	(0.224)	(0.211)	(0.108)
P_{t-1}^{GAS}	-0.812***	-0.599***	-0.897***	-0.796***	-0.822***	-0.900***
	(0.089)	(0.042)	(0.049)	(0.134)	(0.129)	(0.066)
P_{t-1}^{EUA}	-0.451***	-0.090***	0.041	-0.711***	-0.655***	-0.309**
	(0.164)	(0.023)	(0.089)	(0.246)	(0.241)	(0.123)
e_{t-1}	49.945***	1.145***	15.224***	71.884***	69.610***	34.317***
	(9.201)	(0.141)	(5.001)	(13.783)	(13.422)	(6.847)
Trend	0.006	0.091	-0.005	0.000	-0.008	0.014
Const.	-77.520	-104.760	-47.124	-2.901	-25.767	-105.003
Short-run Dynamics						
	ΔP_t^{GB}	$\Delta \log P_t^{\text{GB}}$	$\Delta P_t^{\text{GB,OFF}}$	$\Delta P_t^{\text{GB,PEAK}}$	$\Delta P_t^{\text{GB,W.DAY}}$	$\Delta P_t^{\text{GB,W.END}}$
EC_{t-1}	-0.552***	-0.573***				
	(0.037)	(0.033)				
EC_{t-1}^{OFF}			-0.559***			
			(0.033)			
EC_{t-1}^{PEAK}				-0.542***		
				(0.038)		
$EC_{t-1}^{\text{W.DAY}}$					-0.748***	
					(0.059)	
$EC_{t-1}^{\text{W.END}}$						-0.930***
						(0.069)
Test for Weakly Exogeneity						
p-values	—	$p = 0.63$	$p = 0.82$		$p = 0.27$	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

raised by £0.82/MWh following a £1/MWh$_e$ increase in the gas price, close to the result in Table 4.2.

Regression (ii) also shows that a 1% increase in the EUA price is associated with a 0.09% increase in the wholesale price. From Table 4.1, the average EUA price was £7.52/tCO_2. Hence a £0.75/tCO_2 (10% of the average) increase in the EUA price is associated with a £0.42/MWh (0.9% of the average) increase in the wholesale price. The impact is slightly higher than the estimates from Table 4.2,[34] but we still could not reject the null that the EUA price has been fully passed through to the wholesale price in the long-run.

A final insight from regression (ii) is that if the GBP/EUR exchange rate falls by a thousand basis points (or by 0.1), one would expect the wholesale price to rise by 11.45%, or equivalently, by £5.29/MWh on average. Again, this is close to the estimator from the preliminary case in Table 4.2, and we do not reject the null that the exchange rate variation has been fully passed-through to the wholesale price.

Peak *v.s.* off-peak

In order to investigate whether the PTR depends on the underlying period of the day, Regression (iii) distinguishes peak (07:00-23:00, WET/WEST) and off-peak (23:00-07:00, WET/WEST) periods.[35] We calculate the daily average peak and off-peak wholesale prices to replace P_t^{GB} in $\boldsymbol{y}_t$ (in equation (4.8)), hence we have $\boldsymbol{y}_t = (P_t^{\text{GB,OFF}}, P_t^{\text{GB,PEAK}}, P_t^{\text{COAL}}, P_t^{\text{GAS}}, P_t^{\text{EUA}}, e_t)'$, where $P_t^{\text{GB,PEAK}}$ and $P_t^{\text{GB,PEAK}}$ represent the average peak and off-peak wholesale prices for day t. In other words, we use one structural VECM to estimate peak and off-peak effects simultaneously. The Johansen cointegration tests suggest two cointegrating equations in Regression (iii),[36] which is intuitive because one would expect one cointegratng equation for peak periods, and another for off-peak periods.

The result from regression (iii) suggests that the time of the day has little impact on the long-run relationship between fuel prices and the wholesale price. However, during off-peak periods, the effect of the EUA price on the wholesale price is not significantly different from zero, while during peak periods, the effect is 54% greater than the estimate from the preliminary case (Table 4.2). (Recall that in the preliminary case, we estimate the average pass-through rate over peak and off-peak.) Consequently, this gives a close-to 0% EUA price PTR for off-peak periods, while a greater-than 100% EUA price PTR for peak periods.[37]

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[34] 0.42/0.75=0.56 against 0.46.

[35] The results are not sensitive to the definition of peak and off-peak hours.

[36] See Appendix C.3 for test statistics.

[37] The peak EUA price PTR is 164% if all marginal supply from imports and pumped storages comes from CCGTs, and 136% if all comes from coal plants.

The difference between the peak and off-peak exchange rate PTRs are also statistically significant. Given that the average wholesale prices during the period of study are £38.59/MWh and £50.06/MWh for off-peak and peak periods, the exchange rate PTR is 40%(s.e.=23%) for off-peak periods and 135%(s.e.=28%) for peak periods.

Finally, we fail to reject the null that the rates of adjustment (for the wholesale price towards long-run equilibrium) are identical between peak and off-peak. Specifically, off-peak prices converge to their long-run equilibrium (EC_{t-1}^{OFF}) at a rate of 55.9%, while peak prices converge to their long-run equilibrium (EC_{t-1}^{PEAK}) at a rate of 54.2%.

Weekdays *v.s.* weekends

Regression (iv) investigates heterogeneous PTRs between weekdays and weekends. To do this, we further aggregate the daily data into weekly data based on weekdays and weekends. Then, we obtain two time-series sequences with weekly frequency — one representing weekdays and the other representing weekends. We also aggregate the daily data of fuel and carbon prices, exchange rates, as well as other exogenous variables to weekly data,[38] and then construct the VECM, with a vector of dependent variables $\boldsymbol{y}_t = (P_t^{\text{GB,W.DAY}}, P_t^{\text{GB,W.END}}, P_t^{\text{COAL}}, P_t^{\text{GAS}}, P_t^{\text{EUA}}, e_t)'$, where $P_t^{\text{GB,W.DAY}}$ and $P_t^{\text{GB,W.END}}$ represent the average weekday and weekend wholesale prices for week t. Similar to Regression (iii), the Johansen cointegration test suggests two cointegrating equations in Regression (iv),[39] one for weekdays and the other for weekends. The lag length p, suggested by AIC, is set to 1. This is not surprising because in this case, t represents weeks instead of days.

The result shows that weekdays and weekends have little impact on the long-run relationship between fuel and wholesale prices. However, a £1/tCO_2 increase in the EUA price would on average raise the wholesale price by £0.66/MWh during weekdays, but by £0.31/MWh during weekends. Provided the estimates of the MEFs for the GB electricity supply for weekdays and weekends in Appendix C.1, the point estimate of the EUA price PTR during weekdays is 150% if the entire supply from imports and pumped storage comes from CCGTs, or 121% otherwise. The point estimate of the EUA price PTR during weekends is 73% if the entire supply from imports and pumped storage comes from CCGTs, or 58% if it entirely comes from coal. The difference is substantial, though none of the estimates is statistically significantly different from 100%.

The exchange rate PTRs are also different between weekdays and weekends. Given that the average wholesale price is £47.00/MWh during weekdays and £44.29/MWh during

[38] The fuel prices, carbon prices, exchange rates are only available for weekdays, as the trading platforms are closed during weekends. Therefore, the aggregation for those variables are the weekday averages.

[39] See Appendix C.3 for details of the test result.

weekends, the exchange rate PTR is 148%(s.e.=28%) for weekdays and 78%(s.e.=15%) for weekends. Similar to the EUA case, although none of the estimates suggests that the exchange rate PTR is significantly different from 100%, the result does suggest the PTRs are significantly different between weekdays and weekends.

Finally, because one lag in the weekly data is equivalent to seven lags in the daily data, the speed of convergence to the long-run equilibrium is substantially higher using the weekly data relative to the daily data.

Heterogeneity in the cost pass-through: A discussion

In Sections 4.5.2 and 4.5.2, we show heterogeneity in the carbon price and exchange rate PTRs for different time of the day, and different days of the week. The intuition for the heterogeneous PTRs between peak and off-peak is that it is costly for fossil plants to shut down during off-peak and restart during peak. Instead, fossil plants are usually running at minimum load during off-peak and ramp-up to deliver when demand and price rise, achieved by deploying different bidding strategies between peak and off-peak.

During off-peak periods, the utilisation rate of generation capacity is low, meaning that if a CCGT plant bids according to its marginal cost, the system would dispatch other cheaper power plants to meet the off-peak demand. If that is the case, the CCGT plant will have to shut down during the off-peak, resulting in much higher total cost. Given this, a better strategy for the CCGT plant is probably to have the off-peak bids lower than its marginal cost, ensuring supplying at the minimum load during the off-peak.

During peak periods, the utilisation rate of generation capacity is high, meaning that the CCGTs can exercise market power to bid at some rates higher than the marginal costs. The CCGTs would have a strong incentive to do so because otherwise, their overall profit would most likely to be negative due to the off-peak loss.

Our estimation results in Regression (iii) suggests that the bidding strategy for fossil plants, especially CCGT plants,[40] is that when bidding for the off-peak supply, they completely ignore the EUA price markups, and ignore some (60% given the off-peak PTR is 40%) of the exchange rate markups. It also suggests that the CCGTs would take gas price markup into full consideration when bidding for both peak and off-peak periods. This is not surprising as gas price constitutes about 70% of the marginal cost of electricity generation from a CCGT plant.[41] During peak periods, however, the CCGTs would over-count the input

[40]Recall that CCGTs set the day-ahead electricity price over 80% of the time.

[41]This is roughly estimated from Table 4.1, by dividing the average gas price by the average GB day-ahead price.

costs from EUA prices (by 36%-64%) and exchange rates (by 35%), to compensate losses from the off-peak operation.

The same logic applies to the heterogeneous PTRs between weekdays and weekends. Electricity demand is lower during weekends than weekdays.[42] To avoid shutting down during weekends, fossil plants, especially CCGTs, would lower their bids during weekends, and compensate their losses through bidding at higher rates during weekdays. Similar to the within-day heterogeneity (peak *v.s.* off-peak), our result from Regression (iv) suggests that when bidding for the weekend supply, the CCGTs would fully count in gas price markups and ignore some of the carbon price and the exchange rate markups. During weekdays, the CCGTs would bid at prices higher than the marginal cost, to compensate the losses from weekends.

4.6 Policy Implications

Recall the preliminary estimation result in Table 4.2 shows that a £1/tCO_2 increase in the EUA price is associated with a £0.46/MWh increase in the GB wholesale electricity price. It also shows that a 0.1 increase in the GBP/EUR exchange rate is associated with a £5.33/MWh increase in the wholesale electricity price.

As shown in Figure 4.2, the GBP/EUR exchange rate fell after the Brexit referendum from an average of 1.29 (1 Jan 2016 - 23 Jun 2016) to an average of 1.17 (24 Jun 2016 - 31 Dec 2016). Our estimation shows that, conditional on fuel and carbon prices, the exchange rate depreciation has raised average electricity prices by £6.40/MWh. Assuming that electricity retailers entirely pass through their wholesale costs to retail prices (and domestic tariffs), and given that the total GB electricity load in 2017 was about 300 TWh,[43] we conclude that the depreciation of GBP (caused by the referendum) led to an increase in GB electricity bills by £1.9 billion in 2017. Given that domestic users (GB households) consumed 35% of the country's total electricity consumption,[44] and that in 2017 there were 26.4 million GB households,[45] the electricity bill for an average household in GB has been increased by an additional £25.2 in 2017, or a 4.1% increase in the average bill.[46]

Note that the referendum results may influence the power price through other channels. In the medium-term, most studies expect a decline in the UK's economic growth (e,g. Schoof

[42] During the period of studying, the electricity load during peak periods is 35.14 GW, and that during off-peak periods is 30.98 GW.

[43] Aggregated from the half-hourly actual electricity load from ENTSO-E Transparency Platform.

[44] See Statista.

[45] See Office for National Statistics.

[46] See Statista.

et al. [133], Tetlow and Stojanovic [146]), which would potentially lower energy demand, resulting in a decline in power price. In the long-term, the impact of Brexit on the labour mobility emerges, potentially resulting in a lack of skilled workers. This may have impact on oil and gas industries, further influencing electricity prices.

On the other hand, anticipating the ETS reform resulted in a drastic increase in average EUA prices, which climbed from £5.16/tCO_2 in 2017 to £14.14/tCO_2 in 2018. The £9/tCO_2 increase in the EUA price is associated with a £4.13/MWh rise in the GB day-ahead electricity price. Assuming the wholesale cost has been fully passed through to retail prices, the anticipation of the MSR has raised the GB electricity bill by about £1.2 billion in 2018. About £420 million of this has been transferred to domestic users, corresponding to a £15.9 per year average increase in the typical household's annual electricity bill. This is equivalent to 2.6% of the average bill in 2018.

The higher electricity bill cased by the ETS reform transfers wealth from the GB consumers to electricity producers, and part of it further transfers to the UK government (who earns the ETS revenue).[47] The impact is expected to be more substantial in the forthcoming decade as the UK's trajectory on the 2030 carbon prices to is £70/tCO_2 relative to the current £40/tCO_2. As consumers (especially households) are less elastic to electricity prices in the short-run, it is challenging to palliate their losses in the short term. However, government regulator may be able to use the carbon tax revenue to make low-carbon investments, transferring wealth back to the consumers. In the long-run, one possible way to alleviate the high electricity bill is to install smart meters and smart household appliances that help achieve greater energy efficiency and conduct demand response, resulting in lower consumer bills (See Chapter 5).

4.7 Conclusion

This chapter assessed how major generation costs have been passed through to electricity prices. We use econometrics to estimate the PTR in the British wholesale electricity market during 2015-2018. We failed to reject the null that the gas price, carbon price, and the GBP/EUR exchange rate have been fully passed through to the electricity price, indicating a functioning competitive GB electricity wholesale market.

We also examine heterogeneity of the PTR between peak and off-peak periods, as well as between weekdays and weekends. The EUA cost and exchange rate PTRs are found to

[47] The welfare transfer caused by the lower GBP/EUR exchange rate is more complicated and some general equilibrium models might be preferable. A direct intuition is that the welfare transfer goes to the EUR users as EUR appreciated relative to the GBP.

be higher when electricity demand and generation capacity utilisation rates are high, which most notably occurs during peak as opposed to off-peak periods. This is because it is costly for fossil generators to shut down and then start up again, hence generators are more likely to bid a lower price (than the marginal costs) during off-peak hours in order to maximise overall profit. On the other hand, the utilisation rate of generation capacity is high during peak periods, indicating that fossil-fuelled generators are able to exercise market power, in which case they will bid higher than its marginal costs when supplying at peak hours. We use our econometric results to extend this argument, showing that during off-peak periods, fossil plants' bids are mainly based on fuel costs, while during peak periods, they vary with both fuel, carbon costs, and exchange rates.

The study also considered how the depreciation of sterling since the 2016 Brexit referendum and the introduction of the recent ETS reform have affected electricity prices in GB. We estimated that the referendum resulted in an average increase in GB electricity wholesale prices of £6.40/MWh. In other words, the vote has led to an increase in electricity costs for the average British household by £25.2 in 2017, corresponding to a 4.1% rise. On the other hand, the ETS reform has resulted in a £4.13/MWh increase in the GB electricity price in 2018. This means that an average GB household would need to pay £15.9 (or 2.6%) on top of its current electricity bill due to the associated increase in the EU carbon price.

Chapter 5

Dynamic Tariffs, Demand Responses, and Regulations in Retail Electricity Markets: an agent-based model

5.1 Introduction

The United Kingdom's (UK's) carbon targets anticipate that high levels of renewable energy (wind and solar) production will displace fossil generation. The generation of renewable energy, however, is variable and difficult to predict. Increases in the penetration of renewables will result in high variability in the residual demand (i.e. total demand minus production from renewables), which can further influence wholesale prices. One possible solution is demand response (DR), which seeks to balance supply and demand by providing financial incentives to shift or reduce peak load to off-peak periods. Despite controversy among researchers about DR's costs and benefits, Bradley et al. [22] found DR to produce net positive economic welfare in the UK electricity market. As DR targets electricity consumers, the direct impact of DR is more evident in the retail market than in the spot market (e.g. Balijepalli et al. [11], Woo et al. [159], Yan et al. [162]).

Electricity retailers buy electricity from the wholesale market and resell it to consumers. While they can hedge wholesale prices, retailers are unable to use flat tariffs to hedge against risk and uncertainty of demand; for this reason, they cannot hedge their exposure to spot and balancing prices. As a result, dynamic tariffs such as time-of-use (TOU),[1] critical peak

[1] Under the TOU tariff, a day is separated into several periods, and each period has different price rates. The TOU may refer to either fixed or dynamic TOU, the difference is whether the prices differ for the same period across days.

pricing (CPP),[2] and real-time pricing (RTP)[3] are advocated as means of aligning retail prices with spot market prices (SMPs), thereby transferring some retailer-centred risk to customers.

The rollout of smart meters can significantly facilitate the implementation of dynamic tariffs in two respects. First, retailers can learn how consumption responds to varying prices, and in addition data on demand response can be used to inform the design of more efficient and targeted dynamic tariffs. Second, smart meters (and in-house displays) can provide consumers with information about energy prices ahead of time, and thus, significantly improve the transparency of dynamic tariffs.

The first aim of this chapter is to examine the impact of dynamic tariffs on the retail electricity market, in terms of retail profit, consumer demand and bill, and market gain. It does so by leveraging an agent-based model to derive time-varying retail electricity prices that maximize retail profit and the corresponding demand. We assume that an electricity retailer supplies electricity to households who initially face a flat tariff. The retailer then offers households a dynamic tariff with prices varying on a daily basis, while ensuring that households will prefer the dynamic tariff over the flat tariff (on account of paying smaller electricity bills). Each day, the retailer sets the dynamic tariff to maximize its profit, conditional on households' decisions regarding how much electricity to consume.

The second aim is to determine how the impact of dynamic tariffs varies with market regulation, consumer elasticities, and demand-side management (DSM) stimuli. For example, market regulations that look to establish a more competitive retail market will manifest as a curtailment of the retailer's maximum revenue, and DSM stimuli (such as changing from bi-monthly to monthly bills) will manifest as reduced consumer demand.

This chapter is structured as follows. Section 5.2 summarizes the literature on the impact of dynamic tariffs, and Section 5.3 formulates our agent-based model. Section 5.4 discusses the data used herein. Section 5.5 sets up the default input parameter values that are used as a baseline, and Section 5.6 presents solutions derived by the agent-based model, as well as model extensions. Section 5.7 studies the value-added of demand forecast accuracy. Section 5.8 discusses challenges when facing heterogeneous consumers. Finally, Section 5.9 offers concluding remarks.

[2]Under the CPP tariff, only peak prices are varying across days, and in most days, peak prices is higher than other periods.

[3]Under the RTP tariff, prices are varying hourly or even half-hourly.

5.2 Literature Review on Dynamic Tariffs

Dynamic tariffs were initially implemented in industrial sectors to address large and controllable loads, while incurring relatively low costs per control point (Roos [131]). Starting in 2003, a number of pilot studies examined the impact of household-level dynamic tariffs. Faruqui and Sergici [59], for example, surveyed 15 pilot studies, two of which considered the RTP tariff as a treatment group. Both of these RTP pilot studies demonstrated that RTP tariffs outperform flat tariffs in terms of peak demand reduction and lower household-level electricity bills.

However, studies on European households found that households are sceptical about smart meters and dynamic tariffs and worried about an increase in their electricity demand and bills (Shirani et al. [139], Chamaret et al. [35]). Shirani et al. [139], therefore, argued that smart metering programmes should target on voluntary consumers to avoid conflict of interests. Batalla-Bejerano et al. [14], in reviewing several empirical papers, concluded that consumers exhibit heterogeneous engagement in DR programmes. The degree of engagement depends on "the level of household income, the energy characteristics of the home, the number and composition of the family unit, and the degree of environmental concern and attachment"(p.11).

In terms of the effect of dynamic tariffs on costs and benefits, Borenstein et al. [19] analysed the risks that industrial consumers face on account of fluctuating electricity bills. They found that for these customers, forward-purchase contracts can reduce bill volatility by more than 80%. Nezamoddini and Wang [105] also studied industrial consumers, and they found that although savings realized by switching to dynamic tariffs are programme-dependent, in the majority of cases, consumers see real savings. Roldán Fernández et al. [130] studied the financial benefits of RTP tariffs among Spanish domestic customers and found that dynamic tariffs reduce average electricity prices on account of reduced demand and shifted loads. In a Swedish DR field trial that covered 136 households, Nilsson et al. [107] found that DR varies widely across household types. They also argue that financial incentives, such as dynamic tariffs, constitute the most effective strategy by which to increase demand flexibility. A study on Finnish households, delivered by Ruokamo et al. [132], found that households requires considerable compensation to choose dynamic over flat tariffs.

A number of studies speak to the benefits of dynamic tariffs in terms of retail profit. Nojavan et al. [108] studied the impact of different price schemes on retail profit and suggest that RTP results in higher profit. Zugno et al. [164] found that even though RTP tariffs reduce retail costs relative to TOU tariffs, the latter is more efficient in redistributing consumer demand. Doostizadeh and Ghasemi [52] suggested that in comparison with directly posting the day-ahead wholesale prices to consumers, the proposed day-ahead RTP would be more beneficial for energy retailers and consumers alike. Not all studies suggest that dynamic tariffs will boost retail profit. Dagoumas and Polemis [47], for example, combined a unit-commitment dispatch model and an econometric model and argue that DR will result in changes in the wholesale price, which will in turn impose risk upon retailers. Consequently, DR can lead to retailer losses in some periods, and thus strongly affect retailer viability.

Dynamic tariffs and DR are also thought to have considerable environmental potential. On one hand, the increasing market penetration of variable renewable energy increases imbalance volumes and related costs. DR may be one of the most efficient solutions to this problem (Pina et al. [124], Balijepalli et al. [11]). On the other hand, if the marginal fuels used during peak periods are those that have higher carbon intensity, peak load shifting will help reduce greenhouse gas emissions. Holland and Mansur [82] found that the implementation of the RTP tariff reduces greenhouse gas emissions in some US regions where peak demand is met mainly by oil-fired capacity.

5.3 Model

We start from the premise that the retailer's primary objective is to set dynamic tariffs so as to maximize its expected profit. In Section 5.3.2 we introduce the consumer surplus-maximization problem for a representative household which allows us to derive consumer demand as a function of retail prices. The demand function is then used as a constraint in the retailer's objective function. Section 5.3.3 introduces a number of additional constraints.

In the remainder of this chapter, unless otherwise specified, the term 'dynamic tariffs' refers to day-ahead RTP tariffs, where consumers are informed on electricity prices one day in advance. The proposed RTP tariff can vary on an hourly or even half-hourly basis, and can vary across days.[4]

5.3.1 The Retailer's Problem

Retailers buy electricity from the spot market and resell it to consumers. We assume that, initially, all retailers in the market offer a uniform flat tariff. We then assume a single retailer $\mathscr{A}$ decides to introduces a dynamic tariff, while other retailers continue to offer the original flat tariff. The objective for retailer $\mathscr{A}$ is to maximize the expected profit with day-ahead RTP tariffs under certain market regulation rules (which will be discussed later in Section 5.3.3).

[4] In contrary, TOU tariffs offer the same prices across days.

In this subsection, we first introduce the retailer's profit function, $\phi(\mathbf{x})$, for a given day and household is[5]

$$\phi(\mathbf{x}) = \sum_{t=1}^{T} \{\pi_t d_t - \pi_t^s E_t^s - \pi_t^{\uparrow} \Delta E_t^{\uparrow} + \pi_t^{\downarrow} \Delta E_t^{\downarrow}\}, \tag{5.1}$$

where $t = 1, \ldots, T$ represents periods of the day,[6] and $\mathbf{x} = \{\pi_t, d_t, E_t^s, \Delta E_t^{\uparrow}, \Delta E_t^{\downarrow}\}$.

$\phi(\mathbf{x})$ comprises three parts. The first part, $\pi_t d_t$, denotes the revenue from the retail market, with π_t denoting the retail price and d_t the consumer demand. The second part, $\pi_t^s E_t^s$, denotes the cost of purchasing electricity from the day-ahead spot market, with π_t^s denoting SMPs and E_t^s denoting energy contracted on the day-ahead market. The third part, $\pi_t^{\uparrow} \Delta E_t^{\uparrow} - \pi_t^{\downarrow} \Delta E_t^{\downarrow}$, evaluates losses from the real-time balancing market: $\pi_t^{\uparrow}$ and $\pi_t^{\downarrow}$ respectively denote the balancing prices for the purchasing and selling of electricity; $\Delta E_t^{\uparrow}$ and $\Delta E_t^{\downarrow}$ denote the amount of energy purchased and sold on the balancing market.[7] We assume that Retailer $\mathscr{A}$ has no market power to alter wholesale prices, and so π_t, $\pi_t^{\uparrow}$, $\pi_t^{\downarrow}$ are all exogenous.

The market-balancing condition

$$d_t = E_t^s + \Delta E_t^{\uparrow} - \Delta E_t^{\downarrow}, \quad \forall t, \tag{5.2}$$

guarantees that supply meets demand. We impose the constraint

$$\pi_t^{\uparrow} > \pi_t^s > \pi_t^{\downarrow}, \quad \forall t,$$

which says that in any time period t, the purchase (sell) price in the real-time market must be higher (lower) than the day-ahead market prices. Given this constraint, the retailer will avoid trading on the real-time market, as doing so will always result in lost profit. As such, the expected electricity trading at the real-time balancing market would be zero, or $\mathbb{E}[\Delta E_t^{\uparrow}] = \mathbb{E}[\Delta E_t^{\downarrow}] = 0$.

Taking the expectation of $\phi(\mathbf{x})$ in (5.1), the expected day-ahead profit from the representative consumer takes the form

$$\mathbb{E}[\phi(\mathbf{x})] = \sum_{t=1}^{T} \{\pi_t \mathbb{E}[d_t] - \pi_t^s E_t^s\}, \tag{5.3}$$

[5] Our modelling of the retailer's profit maximization problem is based on the work of Zugno et al. [164].

[6] t could represent (half-)hours. It could also represent periods, such as peak and off-peak periods.

[7] Note that, in reality, wholesale contracts range from years ahead to real time, and there could be several intraday markets between day-ahead and real-time markets. However, in the current study, we simplify the wholesale market such that it consists only of a day-ahead spot market and a real-time balancing market.

with the market-balancing constraint

$$\mathbb{E}[d_t] = E_t^s. \tag{5.4}$$

In reality, the retailer does not know what the actual demand will be on the next day, therefore it decides the amount to bid in the day-ahead market based on demand forecasts.[8] In our empirical analysis, we assume the retailer can perfectly forecast the consumer demand – except in Section 5.7, where we examine the impact of forecast accuracy on retail profit.

5.3.2 The Consumer's Problem

This section sets out the consumer surplus-maximization problem for a representative consumer, and derives consumer demand as a function of retailer prices. We start by assuming there are neither cross-price effects nor DSM stimuli.

By definition, the consumer surplus S_t for a representative household is the difference between the household benefit (from consuming electricity) and electricity bill

$$S_t = B(d_t) - d_t\pi_t, \tag{5.5}$$

where d_t denotes the amount of electricity consumed in period t, π_t denotes retail price in the period t, and $B(d_t)$ denotes the consumer's benefit.

Households aim to maximise the consumer surplus. Therefore, taking the first-order condition of S_t with respect to d_t and setting it to 0, we find

$$\frac{\partial S_t}{\partial d_t} = \frac{\partial B(d_t)}{\partial d_t} - \frac{\partial d_t\pi_t}{\partial d_t} = 0 \tag{5.6}$$

which implies

$$\frac{\partial B(d_t)}{\partial d_t} = \pi_t. \tag{5.7}$$

From (5.7) we observe that at the optimum, the marginal benefit from consuming electricity equals the retail price.

We assume the consumer benefit, $B(d_t)$, is a quadratic function of d_t. Following Schweppe et al. [134], $B(d_t)$ can be written as

$$B(d_t) = B_{0,t} + \pi_{0,t}(d_t - d_{0,t})\left(1 + \frac{d_t - d_{0,t}}{2\varepsilon_{t,t}\cdot d_{0,t}}\right), \tag{5.8}$$

[8] Here, the retailer need only forecast the aggregate/average demand rather than individual-level demand; doing so is much easier.

where $B_{0,t}$ is the consumer benefit when facing the flat tariff. $\varepsilon_{t,t}$ is consumers' own-price elasticity of demand, defined as

$$\varepsilon_{t,t} = \frac{\pi_{0,t}}{d_{0,t}} \frac{\partial d_t}{\partial \pi_t},$$

where $\pi_{0,t}$ is the flat tariff, and $d_{0,t}$ is the demand under the flat tariff.[9]

The function (5.8) takes the specific quadratic form because of its differentiability. When the consumer faces the flat tariff, $d_t = d_{0,t}$ and $B(d_t) = B_{0,t}$.

Taking the first-order condition of $B(d_t)$ in (5.8) and substituting it into (5.7), the consumer demand is

$$d_t = d_{0,t}\left(1 + \varepsilon_{t,t}\frac{\pi_t - \pi_{0,t}}{\pi_{0,t}}\right). \tag{5.9}$$

If we now extend (5.9) to include cross-price effects, the demand function can be written as

$$d_t = d_{0,t}\left(1 + \varepsilon_{t,t}\frac{\pi_t - \pi_{0,t}}{\pi_{0,t}} + \sum_{t'=1}^{T} \varepsilon_{t,t'}\frac{\pi_{t'} - \pi_{0,t'}}{\pi_{0,t}}\right) \tag{5.10}$$

where $\varepsilon_{t,t'}$ is the cross-elasticity which denotes the percentage change in demand at period t in response to the percentage change in price at period t'.

Recall that the retailer buys electricity from the day-ahead wholesale market based on their forecasts of the next day's consumer demand, namely the expected day-ahead demand (for the representative household), which can be written as

$$\mathbb{E}[d_t] = \mathbb{E}[d_{0,t}]\left(1 + \varepsilon_{t,t}\frac{\pi_t - \pi_{0,t}}{\pi_{0,t}} + \sum_{t'=1}^{T} \varepsilon_{t,t'}\frac{\pi_{t'} - \pi_{0,t'}}{\pi_{0,t}}\right). \quad \forall t. \tag{5.11}$$

From (5.11), the expected demand comprises three components. The first component, $\mathbb{E}[d_{0,t}]$, is the expected electricity day-ahead demand under the flat tariff; the second component captures the own-price effect; and the third component captures cross-price effects.

We can further extend (5.11) to account for the impact of DSM stimuli. We consider two types of stimuli: a financial stimulus and an incentive stimulus. A financial stimulus offers financial rewards such as coupons to stimulate (peak) load shifting; an incentive stimulus refers to sending the customer more frequent energy bills and installing more advanced electricity monitors.

[9] In principle, we do not need the initial price to be a flat tariff, though when solving the empirical problem we do set the flat tariff to be a flat tariff.

In a world where both DSM stimulus are implemented, the expected demand becomes

$$\mathbb{E}[d_t] = \mathbb{E}[d_{0,t}] \left(1 + \varepsilon_{t,t} \frac{\pi_t - \pi_{0,t} + r_t}{\pi_{0,t}} + \sum_{t'=1}^{T} \varepsilon_{t,t'} \frac{\pi_{t'} - \pi_{0,t'} + r_t'}{\pi_{0,t}} \right) \cdot \kappa_t \quad , \forall t. \tag{5.12}$$

where κ_t denotes the discount on demand when an incentive stimulus is implemented, which should be less than 1 in most periods.[10] r_t represents the financial penalty for each unit of electricity consumed.

On the one hand, we assume that an incentive stimulus would proportionally change the consumer demand, hence κ_t acts as a multiplier in (5.12). On the other hand, we assume the financial stimuli to be additive to households' surplus function. Subtracting the financial penalty from (5.5) gives the households' surplus function with financial incentives, or $S_t = B(d_t) - d_t \pi_t - d_t r_t$. Then, by repeating process (5.5)-(5.11), we obtain (5.12).

5.3.3 Modelling the Retail Market

In the previous sections, we introduced the retailer's profit maximization problem subject to the market-balancing constraint (5.4) and the demand function for a representative consumer (5.12).

In addition, we place a restriction on the expected daily demand, as shown in equation (5.13).

$$D^{\text{Min}} \leq \sum_{t=1}^{T} \mathbb{E}[d_t] \leq D^{\text{Max}}. \tag{5.13}$$

The upper bound insures the system from power outages, and the lower bound ensures that the basic needs of the representative household are met.

Many European countries have regulated retail tariffs. AF-Mercados et al. [2] summarises that the EU retail tariff regulation has the following properties. First, retail tariffs should be transparent such that each charged component should be clearly stated in the consumer bill. Second, there should be no discrimination, meaning that all users under the same category and demanding the same network service should be charged the same. Third, retail tariffs should reflect concerns about equity, such that consumers in a low-income area are paying less that the cost of service received. Fourth, the tariff should be easy to understand. Fifth, the tariff should be easy to predict, stable, and consistent.

In our model, households' electricity bill only comes from the dynamic tariff, which manifesst the first property. We assume that all households face the same dynamic rate for

[10] Theoretically, for some periods κ_t can be greater than 1, but we would expect an effective incentive stimulus to lower the total demand.

a certain period of time, hence the second property can be satisfied. To address the third property, we will need information on households' location, which will be missing in the data we use in the empirical part, hence will be ignored in this chapter.

To incorporate the fourth and fifth properties, we impose constraints on retail prices, in the form

$$\pi_t^{\text{Min}} \leq \pi_t \leq \pi_t^{\text{Max}} \quad , \forall t. \tag{5.14}$$

This informs the consumer that the retail prices are bounded hence avoids extreme pricing.

We also introduce a constraint which restricts the expected daily bill under the dynamic tariff to be no greater than a proportion (δ) of the expected daily bill under the flat tariff, for the representative household. We write this as

$$\sum_{t=1}^{T} \mathbb{E}[d_t]\pi_t \leq \delta \cdot \sum_{t=1}^{T} \mathbb{E}[d_{0,t}]\pi_{0,t} \tag{5.15}$$

(5.15) has three different economic interpretations. First, δ may represent consumers' risk aversion towards fluctuations in electricity prices, providing an incentive to switch from the flat to the dynamic tariff. A small value of δ then reflects a high level of risk aversion. Second, δ can be interpreted as the level of competition in the electricity retail market: a small value of δ indicates less retail revenue and profit, and hence a more competitive market. Third, δ may represent the extent of regulation in the retail electricity market is, with a small δ indicating that the market is being strictly regulated and retailers are restricted from obtaining high revenues.[11]

[11] An alternative constraint is $\sum_{t=1}^{T} \mathbb{E}[d_t]\pi_t \leq \delta \cdot \sum_{t=1}^{T} \mathbb{E}[d_t]\pi_{0,t}$ – which, if $\delta = 1$, ensures consumer's expected bill under the dynamic tariff is no more than the expected bill if they consume the same demand under the dynamic tariff but pay the flat rate. The difference is that equation (5.15) is an *ex-ante* constraint while the alternative is an *ex-post* constraint. The reason we choose the *ex-ante* constraint (5.15) is that it gives δ three different interpretations, while if we use the *ex-post* constraint, the interpretation of market competitiveness fails, because the right-hand-side formula no longer represent consumer's outside option – switching back to the original flat tariff.

In summary, the retailer's objective function (5.3) subject to market constraints (5.4), (5.14), and (5.15), along with demand constraints (5.12) and (5.13) can be written as

$$
\begin{aligned}
\max_{\mathbf{x}} \quad & \mathbb{E}[\phi(\mathbf{x})] = \sum_{t=1}^{T} \{\pi_t \, \mathbb{E}[d_t] - \pi_t^s E_t^s\}, \\
\text{subject to} \quad & \mathbb{E}[d_t] = E_t^s, \quad \forall t \\
& \mathbb{E}[d_t] = \mathbb{E}[d_{0,t}] \left(1 + \varepsilon_{t,t} \frac{\pi_t - \pi_{0,t} + r_t}{\pi_{0,t}} + \sum_{t'=1}^{T} \varepsilon_{t,t'} \frac{\pi_{t'} - \pi_{0,t'} + r_t'}{\pi_{0,t}} \right) \cdot \kappa_t, \quad \forall t \\
& D^{\text{Min}} \leq \sum_{t=1}^{T} \mathbb{E}[d_t] \leq D^{\text{Max}} \\
& \pi_t^{\text{Min}} \leq \pi_t \leq \pi_t^{\text{Max}}, \quad \forall t \\
& \sum_{t=1}^{T} \mathbb{E}[d_t]\pi_t \leq \delta \cdot \sum_{t=1}^{T} \mathbb{E}[d_{0,t}]\pi_{0,t}.
\end{aligned}
\tag{5.16}
$$

Recall that $\mathbf{x} = \{\pi_t, d_t, E_t^s, \Delta E_t^{\uparrow}, \Delta E_t^{\downarrow}\}$. We solve the profit maximization problem using the barrier method, which formulates the inequality constrained problem as an equality constrained problem, such that Newton's method can be applied (see Appendix D.1 for details). To solve the profit maximization problem. We use consumer demand under a flat tariff ($d_{0,t}$), elasticities ($\varepsilon_{t,t}$ and $\varepsilon_{t,t'}$), and day-ahead SMPs (π_t^s) as input data. We then examine how the proposed dynamic prices that maximize retail profit impact consumer demand and bills, as well as market gain.

5.4 Data

This section describes the datasets used as inputs into the agent-based model, most of which come from the Ireland Electricity Smart Metering Trials (IESMT) programme. Smart meters were installed to record households' half-hourly electricity demand between 14 July 2009 and 31 December 2010, with 3,639 households participating in and completing the trial. Before 2010, all households were offered the standard Electric Ireland flat tariff of 14.1 euro cents/kWh, and in the entire year of 2010, households have been randomly allocated into treatment and control groups. Households in the treatment group face different TOU tariffs, while households in the control group pay the original flat tariff.

Table 5.1 summarizes the tariff groups, tariff structure, and numbers of participants (i.e. households) with complete records. The trial consisted of six different types of tariff schemes

Table 5.1 TOU Tariff Schemes

	Prices by Tariff Scheme (Euro Cents/kWh)					
	A	B	C	D	W	Control
Weekday Off-peak 23.00–08.00	12.00	11.00	10.00	9.00	10.00	14.10
Weekday Shoulder 08.00–17.00 & 19.00–23.00	14.00	13.50	13.00	12.50	14.00	14.10
Weekday/Holiday Peak 17.00–19.00	20.00	26.00	32.00	38.00	38.00	14.10
Weekend/Holiday Off-peak 23.00–08.00	12.00	11.00	10.00	9.00	10.00	14.10
Weekend Shoulder 08.00–23.00	14.00	13.50	13.00	12.50	10.00	14.10
No. of Households	1010	382	1018	373	74	782

– namely, four TOU tariff schemes (A-D), a weekend tariff scheme (W), and one flat tariff scheme (control). Given the design of the trial, among the four TOU tariff schemes, a high peak price always comes with low shoulder and off-peak prices.

Households who face TOU tariffs (Plans A-D) are also randomly allocated in terms of the following four incentive DSM stimuli (CER [33]).

- A bi-monthly electricity bill with a detailed energy statement;
- A monthly electricity bill with a detailed energy statement;
- A bi-monthly electricity bill with a detailed energy statement and an electricity monitor; or
- A bi-monthly electricity bill with a detailed energy statement and an overall load reduction incentive.

Among the four DSM stimuli, households with bi-monthly bills are facing the weakest DSM stimulus among all households.

The impact of the Irish trial (in particular the TOU tariffs and DSM stimuli) on households' electricity demand are well documented by others (e.g. Cosmo et al. [44], Kiguchi et al. [90], O'Neill and Weeks [118]). Instead of estimating the treatment effects attributed to the introduction of TOU tariffs, we use the IESMT dataset as inputs of our agent-based model that solves the retailer's profit maximisation problem. The solution of the agent-based model allows us to further investigate the effect of dynamic tariffs on the retail electricity market.

In addition to the IESMT dataset, we also collect the half-hourly day-ahead SMP data from the Single Electricity Market Operator (SEMO). We then aggregate the half-hourly

Table 5.2 A Summary of Irish SMPs (Euro Cents/kWh), 2010

	Off-peak	Shoulder	Peak
Mean	3.84	5.70	8.47
Minimum	2.39	3.61	3.18
Maximum	6.53	13.11	30.00

Source: http://www.sem-o.com/

data to daily by periods, hence for each day, there are three prices representing the off-peak, shoulder, and peak SMPs. SMP summary statistics are listed in Table 5.2. Not surprisingly, the average peak SMP is much higher than the average shoulder and off-peak SMP. We also observe some extremely high peak SMP for some winter days. During 2010, the highest peak SMP is 30 euro cents/kWh, about 254% higher than the average peak SMP.

5.5 Baseline Settings

In this section we specify the default values for parameters used as a baseline. The value of some of the parameters will change in later empirical analysis, and we will discuss those changes at that point.

As with the IESMT programme, a day is divided into three periods – namely, the off-peak, shoulder, and peak periods – and a retailer sets dynamic tariffs in each period for each day. Therefore, the subscript $t \in \{O,S,P\}$ represents *O*ff-peak, *S*houlder, and *P*eak, respectively.

Table 5.3 details the default values of input parameters. We first assume the DSM stimuli have no impact on consumer demand; hence, $\kappa_t = 1$, $\forall t$. We also assume $\delta = 1$, meaning that as long as the representative household's electricity bill under the dynamic tariff is less than or equal to the flat tariff, they would prefer the dynamic tariff. We obtain the day-ahead SMPs (π_t^s) from the SEMO introduced in Section 5.4, and the flat tariff ($\pi_{0,t}$) follows the flat tariff in the IESMT programme.

The demand for the representative consumer under the flat tariff ($d_{0,t}$) is represented by the average demand among households under the flat tariff (i.e. the 'Control' group in Table 5.1). We assume that for the representative household under the dynamic tariff, the minimum and maximum household demand (i.e. D^{Min} and D^{Max}) is 5% lower/higher than $d_{0,t}$. This sets the lower and upper bounds for the total electricity demand of the representative household within a day. The number, 5%, has little effect on the model result, because under dynamic tariffs demand is mostly shifted instead of reduced within a day.

Table 5.3 Baseline Setting: Values of Input Parameters

κ_t:	=1
δ:	=1
π_t^s:	day-ahead SMPs collected from SEMO
$\pi_{0,t}$:	=14.1 euro cents/kWh, the flat tariff from the IESMT programme
$d_{0,t}$:	the representative household electricity demand under flat tariff in 2010 from the IESMT programme
D^{Min}:	$0.95 \times \sum_{t=1}^{T} \mathbb{E}[d_{0,t}]$ (euro cents/kWh)
D^{Max}:	$1.05 \times \sum_{t=1}^{T} \mathbb{E}[d_{0,t}]$ (euro cents/kWh)
π_t^{Min}:	$\pi_O^{\text{Min}} = 9$, $\pi_S^{\text{Min}} = 12.5$, $\pi_P^{\text{Min}} = 20$
π_t^{Max}:	$\pi_O^{\text{Max}} = 12$, $\pi_S^{\text{Max}} = 14$, $\pi_P^{\text{Max}} = 38$
$\varepsilon_{t,t}$, $\varepsilon_{t,t'}$:	Table 5.4

The market regulator sets the upper and lower bounds of retail prices (denoted as π_t^{Min} and π_t^{Max}, respectively). However, at the time of writing, the Irish market regulator has not yet published such guidelines. Therefore, in the baseline scenario, the upper and lower bounds are taken from the TOU tariffs from the IESMT programme. For example, the range for off-peak TOU prices is within the interval of $[9, 12]$ (see Table 5.1).

Table 5.4 Elasticities of Demand

	t'		
	O	S	P
$\varepsilon_{O,t'}$	-0.039	0.025	0.014
$\varepsilon_{S,t'}$	0.031	-0.067	0.036
$\varepsilon_{P,t'}$	0.044	0.090	-0.134

In terms of consumers' price elasticities of demand, we assume that elasticities for all households are identical, and will discuss the challenges inherent in modelling scenarios when they are not. We follow Mountain and Lawson [100] who estimated consumer elasticities for different periods of the day in Ontario, Canada.[12] The elasticities for the baseline scenario

[12] This is the only reliable research we can find who estimates own- and cross-price elasticities for households under dynamic tariffs. We are unable to provide reliable estimates of elasticities from the IESMT programme, given the design of the trial: the shoulder and off-peak prices suffer from high collinearity (see the first two rows of Table 5.1). Given this, regression methods will not provide reliable estimates of consumer elasticities. One solution might be to exclude either shoulder or off-peak prices from the regression, but doing so would

are listed in Table 5.4,[13] where $\varepsilon_{t,t'}$ represents the impact prices in period t on the electricity demand in period t'. In section 5.6.3 we vary elasticities and investigate the impact on the retail electricity market.

5.6 Results

This section examines the dynamic tariffs that maximize retail profit, and the associated impact on consumer demand, consumer bill, retail profit, and market gain. As the electricity retailer sets the next day's retail prices based upon the wholesale price,[14] we assume that the solutions of the day-ahead retail prices are independent across days. After obtaining the results for each day, we then aggregate the daily results to the annual results and analyse.

We first analyse the baseline results in section 5.6.1, moving on to a focus on the *ceteris paribus* effects of changing the values of some key parameters on the model results. Section 5.6.2 studies the impact of relaxing the retail price constraints, and section 5.6.3 analyses the influence of price elasticities on the retail market. Section 5.6.4 investigates the impact of market regulation, and section 5.6.5 evaluates the effects of DSM stimuli.

By comparing the results of these changes with the baseline, we can inform both retailers and policymakers of the potential impact of dynamic tariffs and demand response policies on the retail electricity market.

In the remainder of this chapter, unless otherwise specified, peak prices, shoulder prices, and off-peak prices respectively refer to peak retail prices, shoulder retail prices, and off-peak retail prices, all under dynamic tariffs.

5.6.1 Baseline Result

Using the baseline parameters as inputs to the agent-based model (5.16), we obtain dynamic retail prices that maximises the retailer's profit. We then examine the distribution of these prices over the study period and specifically the relationship between the dynamic retail prices and the associated SMPs. We then compare the retail profit, consumer demand, consumer bill, and market gain that arise from the dynamic tariffs to those from the original flat tariff.

result in omitted-variable bias. Attempts have also been made to find appropriate regression methods by which to identify elasticities (e.g. the restricted LASSO), but there has been limited success in this area.

[13] The values are taken from Mountain and Lawson [100], page 196, Table 5 ("Rate Cell 16 Winter"), which separates the day into peak, shoulder, and off-peak periods; there, the definitions for the various periods are similar to those in the IESMT dataset.

[14] Also, the constraints of the agent-based model are all daily constraints.

The distribution of dynamic retail prices

Recall that the retailer maximizes its profit subject to the consumers' incentive constraint (5.15), which sets an upper bound to the retail revenue for a given day.[15] As a result, if the retailer wishes to set a high price for one period, the prices for other periods need to be adjusted. After solving the retailer's profit maximization problem, we examine the distribution of retail prices. Table 5.5 presents a categorization of these prices in terms of a number of cases.

Cases a.1-a.4 are ranked in descending order based upon peak SMP. Case a.1 includes days with high peak SMPs (average 11.94 euro cents/kWh) and correspondingly high peak retail price. Given the incentive constraint (5.15), the shoulder and off-peak prices are equal to their lower bounds (represented by the superscript L) of 9 euro cents/kWh and 12.5 euro cents/kWh, respectively.

The average peak SMPs for Case a.2 are lower than those in Case a.1. The attendant lower peak retail price implies that to maximize profit under the incentive constraint (5.15), the retailer can set shoulder prices to the upper bound (represented by the superscript U) of 14 euro cents/kWh. The off-peak prices are equal to the lower bound of 9 euro cents/kWh.

The average peak SMPs for Case a.3 are the second-lowest among all cases, resulting in relatively low peak retail prices. Again, following the incentive constraint (5.15), lower peak retail prices has the effect that shoulder prices are set equal to the upper bound of 14 euro cents/kWh, and the off-peak prices are above the lower bound of 9 euro cents/kWh.

Among all cases Case a.4 has the lowest average peak SMP among all cases, such that we observe the peak retail price set equal to the lower bound of 20 euro cents/kWh. As with Case a.3, to maximize profit the retailer sets the shoulder price equal the upper bound of 14 euro cents/kWh, and the off-peak retail prices exceed the lower bound of 9 euro cents/kWh in order that the incentive constraint (5.15) binds.

Table 5.5 demonstrates the relationship between peak SMP and the distribution of the retail prices that maximizes the retailer's profit. When the peak SMP is relatively high, setting a high peak retail price becomes the retailer's priority; while when the peak SMP is relatively low, setting a high shoulder retail price becomes the retailer's priority. In Cases a.2-a.4 (when the peak SMP is relatively low), equalising the shoulder retail price to its upper bound is

[15] Recall that the incentive constraint (5.15):

$$\sum_{t=1}^{T} \mathbb{E}[d_t]\pi_t \leq \delta \cdot \sum_{t=1}^{T} \mathbb{E}[d_{0,t}]\pi_{0,t} \tag{16}$$

requires that the consumer bill under the dynamic tariff be no more than that under the flat tariff. Since the expected demand under the flat tariff $\mathbb{E}[d_{0,t}]$ and the flat price $\pi_{0,t}$ are both given, the upper bound for the consumer bill can be treated as a constant.

Table 5.5 Distribution of the Dynamic Retail Prices (euro cents/kWh), Baseline

	Dynamic Retail Prices*			Average Spot Prices			
Case	Off-peak	Shoulder	Peak	Off-peak	Shoulder	Peak	No. of days
a.1	9^L	12.5^L	>29	4.13	5.50	*13.39*	119
a.2	9^L	14^U	(20,29)	3.68	5.96	*7.07*	127
a.3	(9,12)	14^U	(20,26)	3.59	5.55	*5.41*	25
a.4	(9,12)	14^U	20^L	3.74	5.63	*4.93*	94

* The superscript L and U represent the lower and upper bounds, respectively.

not sufficient to bind the incentive constraint (5.15),[16] hence to maximise profit, the retailer would increase retail prices in other periods (peak and off-peak) until the constraint binds.

Comparing dynamic and flat tariffs

By solving the agent-based model (5.16), we obtain the retail prices that maximize the retailer's profit. In this subsection we compare the associated retail profit, consumer demand, consumer bill, and market gain under dynamic tariffs, with the same quantities under the flat tariff.

Table 5.6 compares the impact of dynamic and flat tariffs in terms of the following factors:

- *Retail profit* is the average annual profit for the retailer from the representative household;
- *Consumer bill* denotes the average annual electricity bill for the representative household;
- *Consumer demand* denotes the average annual electricity demand for the representative household;
- *Market gain* measures the average annual monetary gains derived from the dynamic tariff, relative to the flat tariff. This is defined as the additional profit earned by the retailer plus the reduction in the representative household's electricity bill. Market gain for a single day can be expressed as

$$\text{Market gain} = \sum_{t=1}^{T} \{[d_t(\pi_t - \pi_t^s) - d_{0,t}(\pi_{0,t} - \pi_t^s)] + (d_{0,t}\pi_{0,t} - d_t\pi_t)\}, \tag{5.17}$$

[16] Because under the baseline scenario, the upper bound of shoulder retail prices is lower than the flat tariff (See Table 5.3).

where the first term measures the change in the retail profit and the second term represents the change in the consumer bill. Note that $(\pi_t - \pi_t^s)$ is the retailer's profit from each unit of electricity sold.

Table 5.6 Flat Tariff *vs.* Dynamic Tariff, Annual Comparison

	Profit (€)	Bill (€)	Demand (kWh)	Market Gain (€)
Flat Tariff	711.26	1199.34	8506	—
Dynamic Tariff	718.61	1199.34	8526	7.35

From Table 5.6 we observe that under the dynamic tariff the retailer earns an additional €7.35 of annual profit from a representative household . The magnitude is small (1%) relative to the annual profit.[17] However, given that in 2017 the total number of UK households was 27.2 million and the market share for a big electricity supplier like British Gas was 20%,[18] switching to the dynamic tariff could increase its annual profit by about €40 million.

As long as the incentive constraint (5.15) is binding, households pay the same bill under the flat and dynamic tariffs. Given (5.17), we then observe that all market gain comes from the increase in the retail profit. We will show in section 5.6.4 that, despite this, implementing tighter market regulation rules (such as easing the licensing process to become an electricity retailer) can redistribute the market gain. We also note that consumer demand increases by 20 kWh/year, meaning that households are consuming more electricity but paying the same cost. Note that this does not necessary mean that households are better off under the dynamic tariff, as this increase in electricity demand comes with peak load shifting, and they may obtain different utilities in different periods.

Table 5.7 compares the annual consumer demand (for the representative household) under the dynamic tariff to that under the flat tariff, for off-peak, shoulder, and peak periods. Overall, the adoption of dynamic tariffs shifts 13.8% of the peak demand to other periods. This finding is comparable to a number of other studies (e.g. Carroll et al. [28], Cosmo et al. [44], Woo et al. [159]). Relative to the baseline scenario, the dynamic tariff reduces the representative household's peak demand by 156.2 kWh/year/household. 133.4 kWh (or 85%) of this is reallocated to shoulder periods and 42.9 kWh (or 27%) is reallocated to off-peak periods. Note that the reallocation sums to 112% given that the dynamic tariff increases annual demand (see Table 5.6). It is also worth mentioning that the annual electricity demand from the IESMT is much higher than the average electricity demand estimated by CER [34].

[17] Note that other costs such as network costs and operating costs are ignored in the retailer's profit function. Once those costs are taken into account, the number of be much higher than 1%.

[18] See Office for National Statistics and Ofgem.

This is because in 2010 both Britain and Ireland experienced the coldest winter on record, resulting in high demand of electric heating.

Table 5.7 Demand-shifting under the Baseline Settings (kWh/Year)

	Demand		Change	
	Flat	Dynamic	Level Change	% Change
Off-peak	1852.3	1895.2	42.9	2.4%
Shoulder	5519.0	5652.4	133.4	2.4%
Peak	1134.6	978.4	-156.2	-13.8%

In summary, under the baseline settings we find that peak SMPs are a critical factor in determining dynamic retail prices. Given the incentive constraint (5.15) that restricts the retailer's total revenue, a high peak retail price is associated with low shoulder and off-peak prices, and vice versa. We also find that the dynamic tariff is beneficial both in terms of substantially increasing retailer profit and shifting and reducing peak load. Although the retailer gets all the market gain, Section 5.6.4 demonstrates that market regulation can redistribute these gains, resulting in a smaller electricity bill for the representative household.

5.6.2 The Role of Price Constraints

Under the baseline scenario the retail-price constraints (in Table 5.3) are based upon values used in the Irish trial. In this section, we widen the range between the lower and upper bounds of the retail prices to allow the retailer more freedom in setting retail prices. Relative to the baseline scenario, we reduce (increase) the lower (upper) bound by 2 euro cents, or

$$\pi_O^{\text{Min}} = 7 \text{ euro cents/kWh} \quad \text{and} \quad \pi_O^{\text{Max}} = 14 \text{ euro cents/kWh}; \tag{5.18}$$

$$\pi_S^{\text{Min}} = 10.5 \text{ euro cents/kWh} \quad \text{and} \quad \pi_S^{\text{Max}} = 16 \text{ euro cents/kWh}; \mathit{and} \tag{5.19}$$

$$\pi_P^{\text{Min}} = 18 \text{ euro cents/kWh} \quad \text{and} \quad \pi_P^{\text{Max}} = 40 \text{ euro cents/kWh}. \tag{5.20}$$

Table 5.8 present the distribution of retail prices that maximizes the retail profit under the price constraints (5.18)–(5.20). Similar to the baseline scenario, we classify the set of solved retail into a number of cases based upon average peak SMPs.

Case b.1 consists of precisely the same days as those in Case a.1 (Table 5.5), indicating the robustness of our model to peak SMPs. Given that the retail price constraints are less restrictive, this allows the retailer to further increase the peak retail price until it equals the upper bound (i.e. 40 euro cents/kWh). Given the nature of the incentive constraint, the retailer will again lower the off-peak retail price to its lower bound (i.e. 7 euro cents/kWh). The retailer will then continue to increase the shoulder retail price until the incentive constraint (5.15) binds.

Table 5.8 Distribution of Dynamic Retail Prices (euro cents/kWh)

	Dynamic Retail Prices*			Average Spot Prices			
Case	Off-peak	Shoulder	Peak	Off-peak	Shoulder	Peak	No. of Days
b.1	7^L	(10.5, 16)	40^U	4.13	5.50	*13.39*	119
b.2	[7^L, 7.4)	16^U	(18,21)	3.67	6.05	*6.86*	121
b.3	[7^L, 8.2)	(15.4, 16^U]	18^L	3.73	5.54	*5.33*	125

* The superscript L and U represent the lower and upper bounds, respectively.

Case b.2 is comparable to Cases a.2-a.3 in Table 5.5, as the shoulder retail prices are equal to their upper bounds while off-peak and peak prices are low. Average peak SMPs are lower than Case b.1 but higher than Case b.3. In this case, shoulder retail prices equal the upper bound at 16 euro cents/kWh, while the peak retail prices is either equal to or greater than the lower bound (i.e. within (18,21) euro cents/kWh).

Finally, Case b.3 is comparable to Case a.4 in Table 5.5, with the average peak SMPs the lowest of all cases, and the peak retail price set equal to the lower bound (i.e. 18 euro cents/kWh). In this case, the shoulder retail price is either equal to or less than its upper bound (i.e. within (15.4, 16] euro cents/kWh), and the off-peak price is either equal to or greater than its lower bound (i.e. within [7, 8.2) euro cents/kWh).

In this case within a day, whenever the shoulder retail price is less than 16 euro cents/kWh, we always observe off-peak retail prices equalling to 7 euro cents/kWh; whenever the off-peak retail price is above 7 euro cents/kWh, we always observe shoulder retail prices equalling to 16 euro cents/kWh. This is not surprising given that the retailer maximises its profit under the incentive constraint (5.15) – while the peak retail price is equal to the lower bound, the retailer makes more profit from setting high shoulder retail prices. For some days, setting the shoulder retail price less than 16 euro cents/kWh is sufficient to bind the constraint (5.15) (because of the low demand or low SMPs), hence we observe shoulder retail prices lower than 16 euro cents/kWh in those days. For some other days, setting the shoulder retail price to 16 euro cents/kWh is not sufficient to bind the constraint (5.15) (because of the high demand or high SMPs), such that the retailer would raise the off-peak retail prices above 7 euro cents/kWh for greater profit.

In comparing Table 5.5 to Table 5.8, we see that the new retail price constraints increase the dispersion of the retail prices. Specifically, the difference in peak retail prices between Cases b.1 and b.2 increases relative to Cases a.1 and a.2. The intuition is that the new constraints allow the retailer to further lower the off-peak retail prices. Because of the incentive constraint (5.15), the retailer can now further increase either the peak or shoulder retail prices – whichever will derive a higher profit. This, in turn, further increases the difference in peak prices between Cases b.1 and b.2.

Table 5.9 shows the retail profit, consumer demand, consumer bill, and market gain from the representative household under the new constraints. Because the new constraints are less restrictive than the baseline scenario, the retail profit almost doubles, from €7.35/year/household to €13.56/year/household. The substantial increase in the retail profit is not surprising because the range between the upper and lower bounds for off-peak (shoulder) periods has more than doubled (tripled).[19]

Due to the incentive constraint (5.15), the consumer bill is still the same as under the flat tariff, but the total demand is substantially reduced by 30 kWh/year (0.35%/year) relative to the total demand under the flat tariff. The intuition is that in the baseline scenario, the upper bounds for both off-peak and shoulder prices are lower than those under the flat tariff.[20] Given that most electricity is consumed during shoulder (and off-peak) periods,[21] the dynamic tariff under the baseline scenario would result in higher demand relative to the flat tariff. However, in the case of new constraints, shoulder retail prices can be higher than the flat tariff, meaning that households would consume less if the shoulder retail price were equal to the new upper bound. Finally, similar to the baseline scenario, all the market gain goes to the retailer.

Table 5.9 Comparing Flat Tariff with Dynamic Tariffs

	Profit (€)	Bill (€)	Demand (kWh)	Market Gain (€)
Flat Tariff	711.26	1199.34	8506	—
Dynamic Tariffs				
Baseline (Table 5.6)	718.61	1199.34	8526	7.35
Constraints (5.18)–(5.20)	724.82	1199.34	8476	13.56

From Table 5.9, consumer demand under the dynamic tariff can be either higher or lower than the flat tariff, depending on the configuration of the dynamic retail price constraints relative to the flat tariff. In our model, whether the demand is higher mostly depends on the

[19] From Table 5.3, under the baseline scenario, the range between the lower and upper bounds for off-peak periods is 3 euro cents/kWh, and for shoulder periods is 1.5 euro cents/kWh. Under the new constraints (5.18)–(5.20), the range for off-peak periods is 7 euro cents/kWh and for shoulder periods is 5.5 euro cents/kWh.

[20] Recall that for the baseline scenario, the upper bound for off-peak retail price is 9 euro cents/kWh and for shoulder retail price is 12.5 euro cents/kWh; while the flat tariff is 14.1 euro cents/kWh.

[21] Peak periods have the highest hourly demand, but off-peak and shoulder periods have the highest overall demand, as they are longer periods.

configuration of the upper bound for shoulder retail prices relative to the flat tariff, because electricity is consumed most during shoulder periods.

Table 5.10 compares electricity demand under the new constraints to that under the flat tariff. For the representative household, the dynamic tariff reduced peak demand by 165.6 kWh in 2010, which is equivalent to 14.6% of peak demand; this is slightly higher than the baseline scenario, at 13.8%. Overall, 46% and 36% of the reduction in peak demand shifts to the shoulder and off-peak periods, respectively. The sum of demand-shifting is 82% given that the dynamic tariff reduces the total demand under the new constraints (see Table 5.9).

Table 5.10 Demand-shifting under Constraints (5.18)–(5.20) (kWh/Year)

	Demand		Demand-Shifting	
	Flat	Dynamic	Level Change	% Change
Off-peak	1852.3	1912.4	60.0	3.2%
Shoulder	5519.0	5595.0	76.0	1.4%
Peak	1134.6	969.0	-165.6	-14.6%

In summary, as the new retail-price constraints give the retailer more freedom in setting the retail prices, the retailer makes more profit, thus amplifying the market gain. In addition, we observe that the representative household reduces more peak load. Again, almost the entire market gain goes to the retailer, but market regulation can redistribute the gain, as Section 5.6.4 shows.

5.6.3 The Role of Elasticities

In sections 5.6.1 and 5.6.2 we examined the impact of dynamic tariffs on the retail market under the baseline scenario, and the impact of less restrictive price constraints. In both cases we used the price elasticities reported by Mountain and Lawson [100], as show in Table 5.4. However, the installation of more advanced smart meters and smart household appliances and the increased use of electric vehicles suggest that consumers, faced with monetary incentives and smart technology, may become be more price sensitive. In this section, we examine the impact of price elasticities on the retail electricity market.

We multiply consumers' elasticities by a factor m that ranges between 1 and 2. Setting $m = 2$, the representative household is twice as elastic as the current level. For different values of m the retailer would set different dynamic tariffs to maximize its profit. This will then generate different levels of consumer demand, consumer bill, and market gain. We examine the impact of elasticities based on two scenarios: the baseline scenario and the scenario with new retail price constraints.

Figure 5.1 demonstrates the relationship between the parameter m and consumer demand, consumer bill, retail profit, and market gain. The solid lines represent the relationships under the baseline scenario, and the dashed lines represent those under the new retail price constraints.

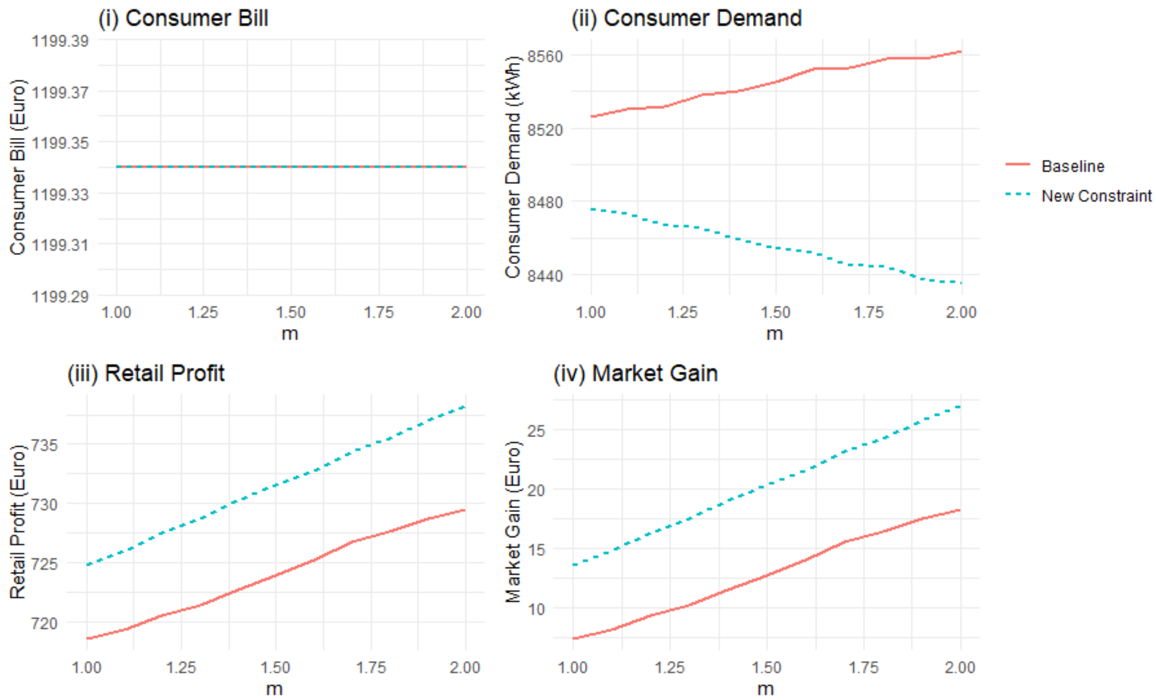

Fig. 5.1 Impact of m on Consumer Demand and Bill, Retail Profit, and Market Gain, Baseline *vs.* New Constraint

Figure 5.1(i) plots the relationship between m and consumer bill. Recall that the incentive constraint (5.15) restricts the maximum bill that the representative household would pay under dynamic tariffs. To maximize profit, the retailer would bind the constraint (5.15); therefore, in both scenarios, the consumer bill under a dynamic tariff will be equal to the bill under the flat tariff, as represented by a horizontal line.

Figure 5.1(ii) shows that under the baseline scenario consumer demand increases with m given that the upper bounds of the off-peak and shoulder retail prices are lower than those under the flat tariff. As a result, the total demand is higher under the dynamic tariff than under the flat tariff. With households being more elastic, they would be more sensitive to off-peak and shoulder retail prices that are consistently lower than those under the flat tariff, thus resulting in higher demand. In this scenario, consumers are paying the same bill as under the flat tariff, but consume more electricity. Whether this makes the consumers better-off depends on whether the utility from enjoying more energy usage exceeds the dis-utility from their peak load shifting.

Under the new retail price constraints (5.18)-(5.20), the upper bound of the shoulder prices is higher than the flat tariff, such that demand under the dynamic tariff will be lower than that under the flat tariff. As m raises and consumers become more elastic, we observe demand negatively related to m. In this scenario, consumers are paying the same bill as under the flat tariff, but consume less electricity, potentially resulting in a reduction in consumer's welfare. However, from policymakers' perspective, less demand means less greenhouse gas emission and greater social benefit. (Estimating the overall impact would require knowledge of households' utilities from consuming electricity, the marginal emission of electricity generation, and the social cost of carbon; these matters are left to future research.)

Figure 5.1(iii) demonstrates the impact of m on retail profit. Note that the retailer makes a profit from buying low and selling high; hence, from the retailer's perspective, the function of a dynamic tariff is to shift the consumer demand from low-profit to high-profit periods. This suggests a positive relationship between m and retail profit. As Subsection 5.6.2 discusses, the new and less-restrictive constraints will allow a retailer to make more profit from households.

Finally, Figure 5.1(iv) presents the relationship between m and the market gain. Recall that the market gain defined in (5.17) is the sum of the increase in the retail profit and the reduction in the consumer bill. Since the retail profit increases with m while the consumer bill stays constant, the market gain fully traces out the retail profit in both scenarios.

In summary, this section shows that a higher retail profit (and market gain) can be obtained from more elastic consumers. This counter-intuition holds because of the incentive constraint (5.15), meaning that the retail profit mainly comes from shifting (elastic) consumers' demand from peak to shoulder and off-peak periods.

We also find that under different retail price constraints, the relationship between consumer demand and consumer elasticities can be in opposite signs (as Figure 5.1(ii) shows). As discussed in Section 5.6.2, the configuration of the retail-price constraints relative to the flat tariff is the key to determine whether consumer demand is upward or downward sloping with consumer elasticities.

5.6.4 The Role of Market Regulation

In this section we relax the assumption that the consumer bill under the dynamic tariff is no more than that under the flat tariff. Instead, we allow δ in the incentive constraint (5.15) to be less than 1.[22] Recall that δ has multiple interpretations, including the level of market

[22]Theoretically, the value of δ can exceed 1, meaning that consumers would pay more under the dynamic tariff than they would under the flat tariff. This would be true if one were to take consumer loyalty into

competition, consumers' risk aversion, and market regulation. The market regulator can intervene via setting market regulation rules to lower the value of δ in accordance with the desire for a more competitive market or more frequent monitoring activities.[23] In this section, we assume that the consumers' risk aversion is held fixed, and a market regulator can lower the value of δ (from the baseline value of $\delta = 1$) through conducting frequent monitoring activities, or through promoting market competition. Therefore, in this case, a smaller δ is associated with a more regulated market or a more competitive market.

Table 5.11 presents the impact of market regulation, in terms of reducing the value of δ, on retail profit, consumer demand, consumer bill, and market gain. We reduce the value of δ until the retailer cannot make more profit from the dynamic tariff relative to the flat tariff. The table shows that the retailer would prefer the flat tariff over the dynamic tariff when $\delta < 0.994$, meaning that if the market is overregulated (i.e. a small δ), the retailer will end up preferring the original flat tariff than dynamic tariffs. This discourage the retailer's incentives to implement dynamic tariffs.

The fact that the variability of market regulation is restricted within the small (in magnitude) interval of [0.994, 1] is not surprising. Recall that the incentive constraint (5.15) sets the upper bound of the consumer bill under dynamic tariffs. For the representative household, this is approximately €1200 (see Table 5.6). A 0.6% reduction in δ is equal to a €7.2 reduction in the representative household's annual bill, or about 98% of the profit that the retailer makes from implementing the dynamic tariff in the baseline scenario (€7.35/year/household).

Table 5.11 Impact of Market Regulation on the Retail Market

	Profit (€)		Bill (€)		Demand	Market
	Profit	Δ^*	Bill	Δ^{**}	(kWh)	Gain (€)
$\delta = 1$	718.61	7.35	1199.34	0.00	8526	7.35
$\delta = 0.998$	716.16	4.90	1196.94	2.40	8524	7.30
$\delta = 0.996$	713.72	2.46	1194.54	4.80	8523	7.26
$\delta = 0.994$	711.27	0.01	1192.14	7.20	8521	7.21
Flat Tariff	711.26	—	1199.34	—	8506	—

Δ^* Difference between dynamic and flat tariff; Δ^{**} difference between flat and dynamic tariff.

From Table 5.11 we see that market regulation has little effect on consumer demand. Although market regulation does slightly sacrifice the total market gain, it transfers market

consideration. However, this violates the perspective that applying dynamic tariffs should make both consumers and retailers better off.

[23] Although we give δ three different interpretations, those interpretations can overlap. For example, market regulation rules can result in a more competitive market.

gain from the retailer to households. The reason is that for a competitive market without externally,[24] the regulator's intervention makes the retail market less efficient. Despite this, at some certain levels of market regulation ($\delta \in [0.994, 1)$ in our model), both the retailer and households benefit from the dynamic tariff, resulting in a win-win condition.

5.6.5 The Role of DSM Stimuli

Allcott [6], Gans et al. [70] each found that DSM stimuli are associated with declines in electricity consumption. In this section we examine the impact of two DSM – switching from monthly to bi-monthly bills and installing in-house displays, both of which were implemented as part of the IESMT programme.[25] Note that from (5.12), the consumer's demand function becomes

$$\mathbb{E}[d_t] = \mathbb{E}[d_{0,t}] \left(1 + \varepsilon_{t,t} \frac{\pi_t - \pi_{0,t}}{\pi_{0,t}} + \sum_{t'} \varepsilon_{t,t'} \frac{\pi_{t'} - \pi_{0,t'}}{\pi_{0,t}} \right) \cdot \kappa_t \quad ,\forall t \in \{O, S, P\}.$$

Recall that κ_t denotes the discount on demand when an incentive stimulus is implemented. Using the IESMT dataset, Cosmo et al. [44] found that relative to bi-monthly bills, monthly bills under TOU schemes reduce peak demand by 1.3%, shoulder demand by 0.2%, and off-peak demand by 1.6%; and installing in-house displays reduce peak demand by 1.0%, shoulder demand by 0.0%, and off-peak demand by 1.2%.[26] Assuming that households react similarly to incentive stimuli under the dynamic tariff and the TOU schemes, we use Cosmo et al. [44]'s results as estimates of κ_t ($t \in \{O, S, P\}$) when switching from bi-monthly to monthly bills, or when installing an in-house display under bi-monthly bills.

Table 5.12 shows the impact of monthly billing and in-house displays on retail profit, consumer demand, consumer bill, and market gain for the representative household. Although both DSM stimuli lower consumer demand, given the incentive constraint (5.15), the consumer bill remains unchanged. The household is then paying the same bill for lower demand, and this results in higher retail profit. This issue can be resolved by regulating the retail electricity market (see section 5.6.4) to transfer the increased market gain to households. The last two rows of Table 5.12 show the results where the DSM stimuli interact with market regulation (by setting $\delta = 0.995$ according to Table 5.11): the household pays lower bills

[24] The retailer electricity market in the UK is considered to be competitive (CMA [42]) and the externalities (mostly CO_2 emissions) of electricity has been properly charged by carbon taxes (See a discussion in Chapter 3).

[25] We do not consider the overall load reduction incentive, because we are unable to determine the precise prices faced by the households affected by that incentive.

[26] See page 130, Table 5, weighted by number of households in each tariff group, divided by the average daily demand for off-peak, shoulder, and peak periods.

Table 5.12 Baseline *vs.* Demand-side Management (DSM) Stimuli

	Profit (€)		Bill (€)		Demand	Market
	Profit	Δ^*	Bill	Δ^{**}	(kWh)	Gain (€)
Baseline	718.61	7.35	1199.34	0.00	8526	7.35
DSM Stimuli						
Monthly Bill	721.73	10.47	1199.34	0.00	8475	10.47
In-house Display	720.48	9.22	1199.34	0.00	8495	9.22
DSM Stimuli & Regulation						
Monthly Bill, $\delta = 0.995$	715.62	4.36	1193.34	6.00	8472	10.36
In-house Display, $\delta = 0.995$	714.37	3.11	1193.34	6.00	8492	9.11
Flat Tariff	711.26	—	1199.34	—	8506	—

Δ^* Difference between dynamic and flat tariff; Δ^{**} difference between flat and dynamic tariff.

with the DSM stimuli, and the retailer also makes higher profit than under the flat tariff. Clearly, this is a win-win condition.

5.7 Forecasting Errors

A retailer buys electricity from the day-ahead spot market and sell it to consumers at the real-time market. As electricity cannot be stored at scale, differences between the volume of retailer's (day-ahead) supply and consumers' (real-time) demand are exposed to the volatile real-time balancing market. In this section, we use our model to measure the value-added of forecasting accuracy (on electricity demand) from the retailer's perspective.

Recall that the retailer profit is the profit from the spot market minus the loss from the balancing market:

$$\phi(\mathbf{x}) = \sum_{t=1}^{T} \{\pi_t d_t - \pi_t^s E_t^s - \pi_t^{\uparrow} \Delta E_t^{\uparrow} + \pi_t^{\downarrow} \Delta E_t^{\downarrow}\}, \tag{1}$$

with the market-balancing constraint

$$d_t - E_t^s = \Delta E_t^{\uparrow} - \Delta E_t^{\downarrow} \quad , \forall t. \tag{2}$$

Recall also that by assuming the SMP is higher than the balancing-market-selling price and lower than the balancing-market-purchasing price ($\pi_t^{\downarrow} < \pi_t^s < \pi_t^{\uparrow}$), the retailer will avoid bidding in the real-time balancing market, i.e. the expected amount of energy purchased from the balancing market is zero ($\mathbb{E}[\Delta E_t^{\uparrow}] = \mathbb{E}[\Delta E_t^{\downarrow}] = 0$).

The retailer's expected profit may then be written

$$\mathbb{E}[\phi(\mathbf{x})] = \sum_{t=1}^{T} \{\pi_t \, \mathbb{E}[d_t] - \pi_t^s E_t^s\}.$$

If the forecast for the next day's demand differs from the actual demand ($\mathbb{E}[d_t] \neq d_t$), either $\Delta E_t^{\uparrow}$ or $\Delta E_t^{\downarrow}$ will be positive, resulting in monetary losses of the form

$$Loss = (\pi_t^{\uparrow} - \pi_t^s)\Delta E_t^{\uparrow} + (\pi_t^s - \pi_t^{\downarrow})\Delta E_t^{\downarrow}. \tag{5.21}$$

The first (second) component of (5.21) denotes the loss from buying (selling) on the balancing market. The greater the volume of balancing market trading ($\Delta E_t^{\uparrow}$ or $\Delta E_t^{\downarrow}$), the greater the monetary losses from forecasting errors.

Forecasting error is usually measured in terms of the mean absolute percentage error (MAPE), which is the average of absolute percentage errors by which the forecasts of a model differ from actual values. Based on the actual difference between day-ahead market and balancing market prices,[27] we assume the balancing-market-selling (purchasing) price is 15% lower (higher) than the SMP, or $\pi_t^{\uparrow} = 1.15\pi_t^s$ and $\pi_t^{\downarrow} = 0.85\pi_t^s$.

We start from simulating a forecast of consumer demand for a representative household for the entire year of 2010, while assuming that the MAPE of the forecast is 10%. Specifically, if the actual electricity demand for a given day, under the dynamic tariff during period t is d_t, we generate a forecast error e_t randomly from a normal distribution:

$$e_t \sim N\left[0, (\eta \cdot d_t)^2\right],$$

where $\eta = \text{MAPE} \cdot \sqrt{\pi/2}$, and here $\text{MAPE} = 10\%$.[28]

The retailer buys electricity from the day-ahead wholesale electricity market based on their forecast of the consumer's electricity demand, or $E_t^s = \mathbb{E}[d_t] = d_t + e_t$. Substituting E_t^s in (2) by $d_t + e_t$, we have $e_t = \Delta E_t^{\uparrow} - \Delta E_t^{\downarrow}$. Note that the retailer can either buy or sell on the balancing market, such that if e_t is positive, the retailer sells the extra electricity at the

[27] In GB in 2013 the average SMP was £50.15/MWh, the average balancing-market-purchasing price was £58.07/MWh, and the average balancing-market-selling price was £43.93/MWh. On average the balancing-market-purchasing price is 15.8% higher than the SMP, and the balancing-market-selling price is 12.4% lower than the SMP. Therefore, the assumption that the balancing price will be 15% lower or higher than the SMP seems to be plausible.

[28] We need to find the value of η such that $\mathbb{E}[|e_t|] = \text{MAPE} \cdot d_t$. Given that the expected absolute value of a normal random variable with mean 0 and standard deviation η is $\eta \cdot \sqrt{2/\pi}$, we solve for η that satisfies $\text{MAPE} = \eta \cdot \sqrt{2/\pi}$, and obtain $\eta = \text{MAPE} \cdot \sqrt{\pi/2}$.

balancing market ($\Delta E_t^{\uparrow} = e_t$ and $\Delta E_t^{\downarrow} = 0$). If e_t is negative, the retailer will purchase more electricity from the balancing market, or $\Delta E_t^{\uparrow} = 0$ and $\Delta E_t^{\downarrow} = e_t$.

Given the actual SMP in Ireland in 2010, all variables in (5.21) are known and we can estimate retailer's annual monetary losses from an representative household. We take 500 simulations of the retailer's annual monetary loss and take the average. Table 5.13 reports the annual loss of profit that the retailer derives from the representative household on account of errors in forecasting electricity demand.

Table 5.13 Forecasting Errors and Retailers' Lost Profit

	MAPEs on $\mathbb{E}[d_t]$			
	10%	5%	2%	1%
Lost Profit (€/year)	7.22	3.61	1.44	0.72

We then compare the retail profit under different MAPE values; the results are also reported in Table 5.13. On average a 1% reduction in the MAPE (i.e. an improvement in the forecast accuracy) is accompanied by an average profit gain of €0.72/year from the representative household, or about €3.9 million/year for a major electricity supplier like British Gas.[29]

In our analysis, we assume that the costs of purchasing and selling electricity in the balancing market are identical (i.e. $\pi_t^s - \pi_t^{\downarrow} = \pi_t^{\uparrow} - \pi_t^s$). However, in a world where they are not identical, the retailer will eventually adjust its forecasts towards the value that minimizes profit loss. For instance, suppose $\pi_t^s - \pi_t^{\downarrow} \leq \pi_t^{\uparrow} - \pi_t^s$; it would then be more profitable for the retailer to purchase a slightly larger amount of electricity than $\mathbb{E}[d_t]$ from the spot market to offset the high cost of purchasing electricity from the real-time market.

5.8 Heterogeneous Consumers: A Discussion

Since households differ in terms of composition and attendant consumption behaviour then similar to the telecom (Oseni and Pollitt [119]) and insurance (FCA [60]) markets, it would be potentially more efficient for the retail market if households were to be differentiated in terms of different dynamic tariff schemes.

However, several issues need to be resolved if one wishes to model the retail electricity market with a retailer that offers different dynamic tariff schemes. First, households are typically allowed to choose their own dynamic tariff scheme over the several schemes

[29]The number of UK households in 2017 was 27.2 million, and in that year, British Gas' share in the electricity retail market was about 20%.

offered by the retailer. If this be the case, our agent-based model (5.16) that assumes all households are facing the same dynamic tariff scheme would not be applicable. A more complicated model, where households can choose over different dynamic tariff schemes, would be preferable. Such model would require some additional model constraints, so as to ensure that a particular group of households would prefer the specific tariff scheme that are targeted to them (so that the retailer's profit gets maximised). If this is not the case, the retailer could be accused of market discrimination.

Second, one needs to decide the number of dynamic tariff schemes in the market, such that the number is sufficiently large to effectively capture household heterogeneity, but not too large so as to make it expensive in terms of computation, management and menu costs. Government regulators such as Ofgem require that retailers set a limited number of tariffs at any point in time (Ofgem [112]).

Finally, one needs to decide upon a clustering technique by which to categorize consumers into different tariff schemes. At the moment, researchers are still debating which clustering technique is most efficient in categorizing electricity consumers (e.g. Figueiredo et al. [64], Tsekouras et al. [149], Chicco [36], Teeraratkul et al. [145]). However, it is not guaranteed that using conventional clustering techniques would categorize consumers with similar elasticities into the same cluster, because almost all techniques use as clustering inputs historical loads, demographic information, or both, rather than elasticities. Therefore, clustering techniques that target household-level elasticities might be preferable.

Given the aforementioned challenges, we leave this work to future research.

5.9 Conclusions

In this study we constructed an agent-based model in which the retailer sets dynamic tariffs so as to maximize profit, and consumers respond to the dynamic tariff. The retailer's profit maximisation problem is based upon (retailer's expected) consumer demand, wholesale electricity prices, consumer elasticities and other factors, and is restricted by consumers' incentives to choose the dynamic tariff over the original flat tariff, as well as some market regulation rules.

Using the model we investigated the impact of dynamic tariffs on the electricity retail market in terms of retail profit, consumer demand and bill, and market gain. We then examined how the impact of dynamic tariffs varies with market regulation, consumer elasticities, and demand-side management (DSM) stimuli, via changing the values of the model's corresponding input parameters.

In the baseline scenario, we assumed there is no DSM stimulus, and that for a representative consumer, the electricity bill under the dynamic tariff is no more than that under the original flat tariff. Our results suggest that by applying the proposed dynamic tariff, the retailer earns from the representative household an additional 1% (€7.35) of annual profit. Although the increase is small relative to the total retail profit, our calculation suggests that in 2017, the implementation of a dynamic tariff would have brought a company like British Gas €40 million of additional annual profit. The proposed dynamic tariff shifts about 13.8% of the peak demand to shoulder and off-peak periods, comparable with other related research.

Our results also suggest that the retailer makes more profit with less-restrictive retail price constraints. This additional profit would hence increase market gain. Market regulations – such as easing the licensing process to become an electricity retailer – may result in a win-win condition by reinforcing a more competitive retail market and transferring some of the retail profit to consumers.

Investigating further we found that the DSM stimuli would reduce consumer electricity demand and under the baseline scenario, bringing more profit to the retailer. Because the DSM stimuli increase the retail profit while market regulations redistribute the retail profit, the interaction between DSM stimuli and market regulation can further reduce consumers' electricity demand, increase retail profit, and lower consumer bills.

We also found that the retailer can obtain higher profit from more elastic consumers, further increasing the market gain from implementing dynamic tariffs. The intuition is that it is challenging for the retailer to use price signals to shift inelastic consumers' demand from low-profit periods to high-profit periods. For this reason, higher retail profit can be obtained from more elastic consumers.

Finally, our agent-based model allowed us to estimate the value-added of improving the accuracy of electricity demand forecasts. Our results demonstrate that a 1% reduction in the mean absolute percentage error on the electricity demand forecast corresponds to a €0.72 increase in the annual retail profit from a representative household, or about €3.9 million/year for a major electricity supplier comparable to British Gas.

In application, it would be challenging to convince households to choose dynamic over flat tariffs unless the retailer guarantees profit sharing. This is possible from the retailer's perspective as our model shows that the dynamic tariff increases retail profit. In a most extreme case where in a perfectly competitive market where all retailers offer dynamic tariffs to consumers, all market gain would go to the consumer. Our results suggest that in the baseline scenario, consumers could pay up to 0.6% less under the dynamic tariff than the flat tariff. The number goes up to 0.8% with DSM stimuli implemented. Note that reducing energy bill is not the main purpose for dynamic tariffs, although the reduction in the electricity bill could lower the burden on households from the increasing electricity bills during the past twenty years due to the increasing fuel costs and carbon prices.

Chapter 6

Conclusion

The United Kingdom's (UK's) Climate Change Act has so far been of a great success. Meanwhile, the UK's economy has been growing at a faster rate than other G7 countries (who have much smaller emissions reduction rate on average), suggesting that carbon mitigation does not necessarily conflict with economic growth.

One of the greatest achievement of the Act is that it has successfully decarbonised the power sector, triggered the Electricity Market Reform (EMR) which aims at decarbonising electricity supply, minimising the cost of energy to consumers, and ensuring the security of supply.

Decarbonising electricity supply

Decarbonisation requires increasing the capacity of renewable energy to phase out carbon insensitive fossil plants, and replacing the more carbon-intensive fossil plants with the less carbon-intensive ones. Its efficacy depends on the cost of emissions reduced. The main EU instrument for setting the price of CO_2 is the Emissions Trading System (ETS). From plausible levels of the allowance (EUA) price of €20-30/tonne in 2008, the price sharply declined after the *Renewables Directive* reduced demand without withdrawing EUAs, and for long periods of time after 2012 has remained well below €10/tonne, at which level it has little effect on the fuel mix and CO_2 emission reduction.

The UK Government has committed to tough carbon limits in the UK *Climate Change Act 2008* and introduced a Carbon Price Floor (CPF) in the 2011 Budget that applies to fossil fuels used to generate electricity. To implement the CPF, the Treasury publishes the Carbon Price Support (CPS, a carbon tax in addition to the EUA price) based on forward EUA prices at the time of the autumn budgets to come into effect at the start of the fiscal year in the following April. The CPS was revised several times to bring the total carbon price up to the announced CPF trajectory that was planned to reach £(2011) 30/tonne by 2020 and £(2011) 70/tonne by 2030. After the failure of other EU countries to either reform the ETS or impose a similar CPF, the Government froze the CPS in 2016 at £18/tonne until 2021.

The impact of this considerable increase in the cost of fossil fuel for electricity generation has been dramatic. Before the introduction of the CPS coal generation was cheaper than the most efficient Combined Cycle Gas Turbines (CCGTs), so that gas was the marginal fuel in the mid-merit part of the market. After the introduction of the CPS, coal eventually became the most expensive fossil fuel (in April 2015, when the CPS increased from £9.55/tonne to £18.08/tonne), causing a massive switch from coal-fired generation to gas. The share of coal fell from 41% in 2013 to 6% in 2018. Great Britain (GB, the CPS does not apply in Northern Ireland) therefore offers an excellent test-bed for the impact of a carbon tax (the CPS) on the electricity market.

Chapter 2 quantifies the impact of the CPS on the carbon savings from wind. Wind is hard to forecast with much accuracy day-ahead, when the time comes to decide which types of generation to commit and run. As wind varies from moment to moment, the carbon displaced will depend on the plant operating and its flexibility. We study this short-run impact econometrically to find the main drivers of the short-run displacement achieved.

Policies are chosen for their long-run impact. Governments set targets for the future share of renewable electricity and carbon budgets. These policies will affect the future fuel mix, and hence the dispatchable plant available daily. We determine this long-run impact with a unit commitment dispatch model of the 2015 GB system. We examine the effect of increasing wind capacity by varying amounts up to 25%. Long run has the conventional meaning that it is a period over which wind capacity can change, in contrast to the short run in which wind capacity is fixed but its output may vary. We study the impact of the CPS in 2015. The first counterfactual has no CPS, but just the EUA price. The second looks at the CPS in 2018 after the EU ETS was reformed, which raised the GB carbon price substantially above its 2015 level.

We find that the CPS lowered the short-run Marginal Displacement Factor (MDF, the CO_2 emission reduced from the last unit of wind generation in MWh/tonne CO_2) by 7% in 2015 but raised the long-run MDF (for a 25% increase in wind capacity) by 18%. We discuss reasons for the modest differences in the short- and long-run MDFs.

Other countries and regions, such as The Netherlands and the island of Ireland, also show interests in adopting a CPF, although the Dutch Parliament failed to pass the vote in 2019. Therefore, using unit-commitment dispatch models of the Dutch and Irish electricity systems to investigate the impact of a CPF on their electricity system would be interesting topics for future research. Future works could also be focus on which level of carbon price and fuel mix are required to completely decarbonise the British power (or electricity) sector in 2050.

Chapter 3 develops a methodology for quantifying the impact of an asymmetric carbon tax on electricity trade within a closed region such as the European Union (EU) and North America. The EU's *Third Electricity Package* came into force in 2014, requiring day-ahead market coupling of interconnectors. Before market coupling, traders had to buy interconnector volume and direction before knowing the market clearing price at each end, often resulting in inefficient trades. Market coupling ensured that interconnector capacity would be cleared at the same time as electricity markets, securing efficient trade. If market prices can be equilibrated without violating interconnector capacity constraints, prices at each end will be the same. Otherwise, trade will be set at full capacity and prices will diverge.

Being a unilateral carbon tax, the CPS can distort electricity trade with external markets. Chapter 3 takes GB as a case study and quantifies the impact of the CPS on electricity prices, interconnector flows, congestion income (from buying low and selling high), and social value from trade. It also estimates the deadweight loss and carbon leakage in the electricity sector created by the asymmetric carbon taxes. This has implications for the design and ideally harmonisation of the EU carbon tax to improve the efficiency of electricity trade.

We estimated that Over 2015-2018, the CPS raised the GB day-ahead electricity price by about €11/MWh, after allowing for replacement by cheaper imports. It raised the French wholesale price by 3.5% and Dutch wholesale price by 2.8%. The CPS increased GB imports by 12 TWh/yr, thereby reducing carbon tax revenue by €100 m/yr. Congestion income increased by €150 m/yr, half transferred to foreign interconnector owners. The unilateral CPS created €80 m/yr deadweight loss, about 32% of the initial social value created by the interconnector, or 4% of the global emissions benefit of the CPS at €2 bn/yr. About 0.9% of the CO_2 emission reduction is undone by France and The Netherlands, the monetary loss of which is about €18 m/yr.

Despite that the UK has officially departed from the EU, there are three more interconnectors (between GB and the Continent) under construction. Under unilateral carbon taxes, more interconnector capacity would further distort the cross-border electricity trading, and eventually, the deadweight loss may exceed the social value of the newly built interconnectors. With more interconnectors being commissioned, it would be interesting to estimate the monetary value of the deadwight loss if the unilateral carbon taxes continue to exist. Furthermore, leaving the EU offers the UK a great opportunity to fix the market distortion via introducing a Carbon Emission Tax or a UK ETS (or a Border Tax Adjustment). The goal is to minimise the deadweight loss from market distortion, and meanwhile, keep decarbonising the energy sector.

Minimising the cost of energy to consumers

A competitive electricity market ensures that consumers pay electricity bills that reflect the actual cost of electricity generation, transmission, and distribution. Policymakers often rely on cost Pass-Through Rates (PTRs) to measure market competition since these can measure the degree to which a change in costs determines a change in prices. An increase in the input cost raises the marginal cost of electricity generation, but generators may absorb part of the increase by marking up their offer by a smaller or larger amount if the market is imperfectly competitive, depending on the shape of the residual demand (i.e. total demand minus renewables) curve. The PTR would then differ from 100%. However, given that consumers are inelastic to wholesale electricity prices in the short-run, a PTR significantly different from 100% would cast doubt on the assumption of competitiveness.

Chapter 4, therefore, investigates a wide range of costs pass-through. In particular, we focus on fuel prices, carbon prices, and exchange rates PTRs. We investigate whether they are consistent with the notion of a competitive British wholesale electricity market. Our investigation is conducted both theoretically and empirically.

Political events and reforms in the United Kingdom (UK) and the European Union (EU) could strongly influence the cost of energy to producers and hence to consumers. The Brexit referendum and the recent EU ETS reform resulted in substantial changes in Sterling exchange rates and carbon prices (respectively), providing an ideal test-bed for studying PTRs.

We employ a sector-level dataset, and use econometrics to estimate long-run relationships between the input cost of electricity generation and the GB wholesale electricity price during 2015-2018. In the theoretical part, we show that the long-run relationships cannot be directly used as PTR. Instead, certain transformations are needed to deliver the estimates of PTRs. For example, we show that the carbon price PTR is equal to the ratio between the impact of carbon prices on electricity prices and the Marginal Emissions Factor (MEF) of the electricity system. Another example is that the fuel price PTR is equal to the ratio between the impact of fuel prices on electricity prices and the marginal share of the fuel. Note that most related empirical literature uses thermal unit-level data to directly estimate the PTR, while we show how to use a much cruder sector-level dataset to estimate the cost pass-through in a wholesale electricity market.

We do not reject the hypothesis that gas prices, carbon prices, and exchange rates are entirely passed through to British wholesale electricity prices. We find heterogeneous PTRs for different times of the day and days of the week, consistent with the argument that this occurs due to electricity generators exercising different bidding strategies over different periods of the day. We extend this argument by discussing generators' actual bidding strategy:

the off-peak bids are mainly based on fuel costs, while the peak bids depend on both fuel and carbon costs. Finally, assuming that the wholesale cost has been fully passed through to the domestic electricity bill, we estimate that the depreciation of GBP associated with the Brexit referendum and MSR have increased the average annual bills by £41/year/household, or a 7% rise.

The national-wide lock-down for COVID-19 has substantially reduced electricity demand, providing another ideal test-bed for monitoring the cost pass-through and generators' bidding strategy. The market structure of electricity generation may also be changed during the pandemic, as the daily load curve is much flatter than it used to be. Hence, peak loading plants such are coal-fired power plants as no longer producing electricity, making CCGTs the only fossil fuel that responds to changes in demand and wind supply.

Ensuring the security of supply

The EMR also aims to ensure the security of electricity supply. One possible solution is demand response (DR), which helps balance supply and demand by introducing load flexibility at the consumer level. DR usually provides consumers with financial incentives to shift or reduce peak load to off-peak periods. As such, the direct impact of DR can be more effective in the retail market as opposed to the spot market.

Electricity retailers buy electricity from the wholesale market and resell it to consumers. While they can hedge wholesale prices, retailers are unable to hedge against demand risk and uncertainty from the retail side using flat tariffs. Hence, neither they can hedge their exposure to spot and balancing prices. As a result, dynamic tariffs such as time-of-use, critical peak pricing, and real-time pricing are advocated as a means to align retail prices with spot market prices, thereby transferring some of retailers' risks to customers.

The first aim of Chapter 5 is to study the impact of dynamic tariffs on the retail electricity market, in terms of retail profit, consumer bill, consumer demand, and market gains. We do this by constructing an agent-based model to derive retail electricity prices that maximises the retail profit and the corresponding demand. We assume that an electricity retailer supplies electricity to some households who initially face a flat tariff. Then, the retailer offers households a new dynamic tariff, with prices varying on a daily basis, while ensuring an average household prefers the dynamic tariff over the flat tariff. Each day, the dynamic tariff is announced one-day-ahead for the following day, and the retailer sets the dynamic tariff to maximise its profit conditional on households' decision on how much electricity to consume. During the whole process, the retailer faces various market regulation rules, such as restrictions on the maximum and minimum retail prices. Those regulation rules are reflected as model constraints in the agent-based model.

The second aim is to evaluate the impacts of market regulation, consumer elasticities, and demand-side management stimuli on the retail market. We demonstrate these impacts by changing the values of the corresponding input parameters in the agent-based model. For example, market regulations aiming to establish a more competitive retail market is reflected as the retailer's maximum revenue being curtailed, and demand-side management stimuli are reflected as a reduction in the consumer demand. Eventually, the solution of the agent-based model would give us different retail prices and the associated consumer bill, consumer demand, and market gains under different parameter values.

The model results suggest that in the baseline scenario, the dynamic tariff brings the retailer an additional €7.35 of annual profit from an average household, or €40 million for a firm as large as British Gas in 2017. With market regulations, the dynamic tariff will benefit both consumers and retailers, resulting in a win-win situation. We also find that the interaction between demand-side management stimuli and market regulation can further reduce consumers' electricity demand, increase retail profit, and lower consumer bills.

One direction to extend the agent-based model is to investigate the scenario where households are allowed to choose over several different dynamic tariff schemes. In that case, households demographic information such as income level and household size might play crucial roles in predicting which tariff scheme a household will choose. On the other hand, due to data availability, Chapter 5 fails to deliver estimates on households' elasticities of electricity demand. This is left for future work.

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Appendix A

Appendix for Chapter 2

A.1 The linear SR-MDF econometric model

In addition to Table 2.3, we also use the linear regressions to study the asymmetric partial effects when wind rises against falls, when the demand on fossil generation increases against declines, and weekdays against weekends. To do this, we run several regressions based on the sign of ΔW_t and $\Delta C_t + \Delta G_t$, and on the day of week. The results are shown in Figure A.1 and A.2. We find the results robust to these factors.

The non-linear regression results are shown in Table A.3.

We aggregate the half-hourly data to daily, and re-run the linear regression. Table A.4 shows the result, which are similar to those in Table 2.3. In this case, the marginal effects of wind and demand on coal and gas sum to about 0.95, higher than the half-hourly case. The reason is well explained in the main body of the paper (See discussion under Figure 2.6 and to the start of Section 2.8). Although coal does respond more to wind and demand changes, the trend of the estimated SR-MDF will not be affected. However, we argue that this is the wrong counterfactual as attributing the fuel source for replenishing pumped storage to wind is arguable at best, and pumped storage actions are primarily driven by system balancing actions which would happen regardless of short-run wind variations.

A.2 Marginal Emission Factor

Table A.5 reports the Marginal Emission Factors (MEF) for each quarters from 2012-2017, estimated from the non-linear regressions. Note that the standard errors are negligible (about 0.001 for all quarters), hence unreported.

Table A.1 Estimate asymmetric partial effects, Off-peak (23:00-07:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
	When wind rises, $\Delta W_t > 0$			
ΔW_t	-0.57^{***}	-0.16^{***}	-0.39^{***}	-0.76^{***}
	(0.04)	(0.02)	(0.04)	(0.03)
ΔD_t	0.42^{***}	0.19^{***}	0.56^{***}	0.75^{***}
	(0.01)	(0.00)	(0.01)	(0.01)
	When wind falls, $\Delta W_t \leq 0$			
ΔW_t	-0.46^{***}	-0.17^{***}	-0.49^{***}	-0.73^{***}
	(0.04)	(0.02)	(0.04)	(0.03)
ΔD_t	0.42^{***}	0.21^{***}	0.53^{***}	0.73^{***}
	(0.01)	(0.00)	(0.01)	(0.01)
	When fossil generation increases $\Delta C_t + \Delta G_t > 0$			
ΔW_t	-0.41^{***}	-0.16^{***}	-0.35^{***}	-0.55^{***}
	(0.04)	(0.02)	(0.03)	(0.02)
ΔD_t	0.33^{***}	0.21^{***}	0.61^{***}	0.69^{***}
	(0.01)	(0.00)	(0.01)	(0.01)
	When fossil generation increases $\Delta C_t + \Delta G_t \leq 0$			
ΔW_t	-0.43^{***}	-0.12^{***}	-0.49^{***}	-0.75^{***}
	(0.02)	(0.01)	(0.02)	(0.02)
ΔD_t	0.40^{***}	0.17^{***}	0.48^{***}	0.69^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
	Weekdays			
ΔW_t	-0.54^{***}	-0.17^{***}	-0.43^{***}	-0.90^{***}
	(0.03)	(0.01)	(0.02)	(0.02)
ΔD_t	0.44^{***}	0.20^{***}	0.40^{***}	0.62^{***}
	(0.01)	(0.00)	(0.01)	(0.01)
	Weekends			
ΔW_t	-0.51^{***}	-0.13^{***}	-0.52^{***}	-0.77^{***}
	(0.03)	(0.02)	(0.03)	(0.02)
ΔD_t	0.48^{***}	0.17^{***}	0.40^{***}	0.72^{***}
	(0.01)	(0.01)	(0.01)	(0.01)

Table A.2 Estimate asymmetric partial effects, Peak (07:00-23:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
	When wind rises, $\Delta W_t > 0$			
ΔW_t	-0.15^{***}	-0.15^{***}	-0.67^{***}	-0.69^{***}
	(0.02)	(0.01)	(0.03)	(0.02)
ΔD_t	0.14^{***}	0.21^{***}	0.63^{***}	0.60^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
	When wind falls, $\Delta W_t \leq 0$			
ΔW_t	-0.12^{***}	-0.14^{***}	-0.64^{***}	-0.61^{***}
	(0.02)	(0.02)	(0.03)	(0.02)
ΔD_t	0.14^{***}	0.21^{***}	0.65^{***}	0.62^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
	When fossil generation increases $\Delta C_t + \Delta G_t > 0$			
ΔW_t	-0.12^{***}	-0.12^{***}	-0.55^{***}	-0.55^{***}
	(0.02)	(0.01)	(0.02)	(0.01)
ΔD_t	0.15^{***}	0.16^{***}	0.54^{***}	0.54^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
	When fossil generation increases $\Delta C_t + \Delta G_t \leq 0$			
ΔW_t	-0.14^{***}	-0.15^{***}	-0.58^{***}	-0.56^{***}
	(0.02)	(0.01)	(0.02)	(0.01)
ΔD_t	0.10^{***}	0.25^{***}	0.69^{***}	0.56^{***}
	(0.00)	(0.00)	(0.01)	(0.00)
	Weekdays			
ΔW_t	-0.01	-0.19^{***}	-0.81^{***}	-0.68^{***}
	(0.01)	(0.01)	(0.02)	(0.01)
ΔD_t	0.29^{***}	0.21^{***}	0.48^{***}	0.55^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
	Weekends			
ΔW_t	-0.09^{***}	-0.15^{***}	-0.73^{***}	-0.70^{***}
	(0.02)	(0.01)	(0.02)	(0.02)
ΔD_t	0.21^{***}	0.19^{***}	0.54^{***}	0.57^{***}
	(0.00)	(0.00)	(0.00)	(0.00)

Table A.3 Estimation results from non-linear regressions (iii) and (iv)

	Off-peak (23:00-07:00)		Peak (07:00-23:00)	
	ΔC_t	ΔG_t	ΔC_t	ΔG_t
(Intercept)	-2.57	11.27	59.08^{***}	38.57^{***}
	(5.22)	(5.76)	(6.48)	(8.72)
ΔW_t	-0.34^{***}	-0.54^{***}	-0.22^{***}	-0.59^{***}
	(0.02)	(0.03)	(0.01)	(0.02)
ΔD_t	0.35^{***}	0.58^{***}	0.23^{***}	0.60^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta W_t \times PD_t$	$2.39 \times 10^{-2***}$	$-2.13 \times 10^{-2***}$	0.05×10^{-2}	-0.09×10^{-2}
	(0.27×10^{-2})	(0.29×10^{-2})	(0.16×10^{-2})	(0.21×10^{-2})
$\Delta W_t \times PD_t^2$	3.26×10^{-4}	$-10.47 \times 10^{-4*}$	$8.30 \times 10^{-4***}$	$-6.47 \times 10^{-4*}$
	(4.12×10^{-4})	(4.55×10^{-4})	(2.41×10^{-4})	(3.24×10^{-4})
$\Delta W_t \times PD_t^3$	$-2.91 \times 10^{-5*}$	$3.04 \times 10^{-5*}$	-0.36×10^{-5}	0.74×10^{-5}
	(1.37×10^{-5})	(1.51×10^{-5})	(0.79×10^{-5})	(1.07×10^{-5})
$\Delta W_t \times PD_t^4$	-0.82×10^{-6}	$3.62 \times 10^{-6*}$	-1.15×10^{-6}	0.48×10^{-6}
	(1.48×10^{-6})	(1.63×10^{-6})	(0.86×10^{-6})	(1.15×10^{-6})
$\Delta D_t \times PD_t$	$-1.86 \times 10^{-2***}$	$1.38 \times 10^{-2***}$	$0.16 \times 10^{-2***}$	$0.10 \times 10^{-2***}$
	(0.03×10^{-2})	(0.04×10^{-2})	(0.02×10^{-2})	(0.03×10^{-2})
$\Delta D_t \times PD_t^2$	$-6.65 \times 10^{-4***}$	$9.84 \times 10^{-4***}$	$-4.80 \times 10^{-4***}$	$1.81 \times 10^{-4***}$
	(0.50×10^{-4})	(0.55×10^{-4})	(0.30×10^{-4})	(0.40×10^{-4})
$\Delta D_t \times PD_t^3$	$3.71 \times 10^{-5***}$	$-2.50 \times 10^{-5***}$	$-1.30 \times 10^{-5***}$	-0.21×10^{-5}
	(0.19×10^{-5})	(0.21×10^{-5})	(0.11×10^{-5})	(0.15×10^{-5})
$\Delta D_t \times PD_t^4$	$0.90 \times 10^{-6***}$	$-1.68 \times 10^{-6***}$	-0.03×10^{-6}	$0.30 \times 10^{-6*}$
	(0.18×10^{-6})	(0.20×10^{-6})	(0.11×10^{-6})	(0.14×10^{-6})
R^2	0.64	0.84	0.48	0.84
Num. obs.	34503	34503	68902	68902

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

A.3 Replicating Thomson et al. [147]

We use the five-minute average generation by fuel data from the Elexon Portal[1] for the year 2009-2016. The replication process can be summarized as follows:

1. Use the same fuel intensity values for coal (0.39988kg CO_2/kWh_{th}) and gas (0.22674kg CO_2/kWh_{th})[2] as Thomson et al. [147], and the average thermal efficiency of 35.6%

[1] See Elexon Portal.
[2] NCV *plus* well-to-tank NCV.

Table A.4 Estimation results from linear regressions (i) and (ii), using daily data

(a) Off-peak period (23:00-07:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
(Intercept)	-6.69	37.54	66.56	31.06
	(54.43)	(52.42)	(52.95)	(57.94)
ΔW_t	-0.61^{***}	-0.10^{***}	-0.29^{***}	-0.76^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
ΔD_t	0.69^{***}	0.26^{***}	0.35^{***}	0.75^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
Time Dummies	YES	YES	YES	YES
R^2	0.79	0.33	0.47	0.86
Obs.	1105	1080	1105	1080

(b) Peak period (07:00-23:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
(Intercept)	54.93	-125.91^{*}	-25.45	107.99
	(77.94)	(62.13)	(80.54)	(65.42)
ΔW_t	-0.20^{***}	-0.19^{***}	-0.73^{***}	-0.77^{***}
	(0.02)	(0.02)	(0.03)	(0.02)
ΔD_t	0.30^{***}	0.25^{***}	0.70^{***}	0.73^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Time Dummies	YES	YES	YES	YES
R^2	0.64	0.62	0.87	0.93
Obs.	1099	1072	1099	1072

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

and 54.5% respectively for coal and gas plants, to calculate the emission factors for coal (1.111kg CO_2/kWh) and gas (0.412kg CO_2/kWh).[3]

2. We use the same emission factors for other generation types as Thomson et al. [147], and extend their Table 2 to 2016. However, although the emission factors for overseas electricity can be found at the IEA website,[4] it is not publicly available, hence we use the overseas emission factors for 2014 to proxy the overseas emission factors for 2015 and 2016.

[3] Thomson et al. [147] argue that the thermal efficiency of a generating unit should be varying with the relative load (i.e. actual load relative to its full capacity), while we are unable to obtain the data for generating units, hence used the average efficiency.

[4] See IEA website.

Table A.5 Marginal Emission Factors

year	season	Peak MEF	Off-peak MEF	Average MEF
2012	Q1	-0.381	-0.551	-0.438
2012	Q2	-0.370	-0.565	-0.435
2012	Q3	-0.369	-0.565	-0.434
2012	Q4	-0.344	-0.561	-0.416
2013	Q1	-0.331	-0.518	-0.393
2013	Q2	-0.354	-0.570	-0.426
2013	Q3	-0.348	-0.566	-0.421
2013	Q4	-0.337	-0.550	-0.408
2014	Q1	-0.346	-0.558	-0.417
2014	Q2	-0.393	-0.524	-0.436
2014	Q3	-0.396	-0.503	-0.431
2014	Q4	-0.371	-0.565	-0.436
2015	Q1	-0.382	-0.551	-0.438
2015	Q2	-0.401	-0.480	-0.427
2015	Q3	-0.401	-0.467	-0.423
2015	Q4	-0.397	-0.441	-0.411
2016	Q1	-0.392	-0.421	-0.402
2016	Q2	-0.392	-0.423	-0.402
2016	Q3	-0.357	-0.384	-0.366
2016	Q4	-0.337	-0.369	-0.348
2017	Q1	-0.350	-0.381	-0.360
2017	Q2	-0.345	-0.371	-0.354
2017	Q3	-0.307	-0.365	-0.327
2017	Q4	-0.326	-0.370	-0.341

3. Now that we have the emission factors for all fuel types, we can calculate CO_2 emissions for each five-minute interval. As in Thomson et al. [147], we set negative imports to zero. However, for reasons given in Section 2.6, we ignore pumped storage.

4. The five-minute changes in wind output (ΔP_w), total system supply (ΔP_s) and total system emissions (ΔC) are calculated as the difference between successive values.

5. After removing outliers, we run the following regression for each year:

$$\Delta C = k_0 + k_1 \Delta P_s + k_2 \Delta P_w + \boldsymbol{h'X_t} + \varepsilon,$$

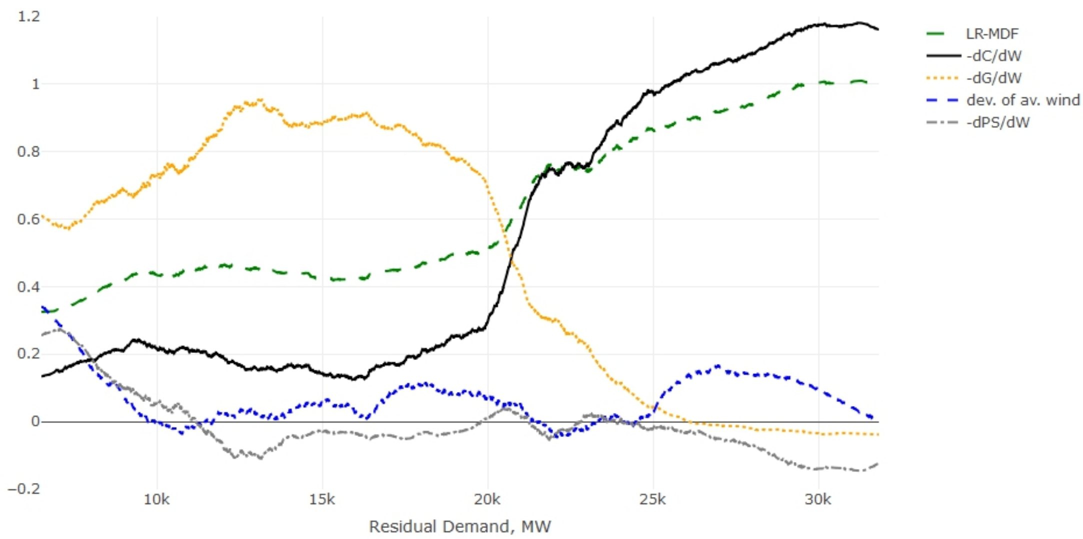
where k_1 is the marginal emission factor (MEF) and k_2 is the marginal displacement factor (MDF).

The results are shown in Table A.6 and Figure 2.9. The numbers following "±" are standard errors multiplied by 1.96.

Table A.6 Comparisons of annual MDFs, tCO_2(eq)/MWh

	MDF (wind)		
Year	Our Estimates	Replicated Results	Thomson et al.
2009		0.650 ± 0.039	0.597 ± 0.065
2010		0.628 ± 0.023	0.611 ± 0.049
2011		0.562 ± 0.022	0.553 ± 0.032
2012	0.436 ± 0.031	0.564 ± 0.018	0.547 ± 0.025
2013	0.426 ± 0.063	0.480 ± 0.012	0.487 ± 0.017
2014	0.430 ± 0.046	0.455 ± 0.010	0.483 ± 0.014
2015	0.413 ± 0.030	0.438 ± 0.009	
2016	0.362 ± 0.031	0.382 ± 0.008	
2017	0.334 ± 0.029		

Fig. A.1 Displacement Factors v.s. Residual Demand, £37/tCO_2



A.4 Figure Appendix

Figure A.1 graphs a rolling average (over 672 non-consecutive hours ranked by residual demand) of the displacement of coal output ($-\Delta C/\Delta W$), gas output ($-\Delta G/\Delta W$), pumped storage output ($-\Delta PS/\Delta W$), and the implied carbon saving, the LR-MDF ($-\Delta CO_2/\Delta W$, tCO_2/MWh) as a function of residual demand (here the summation of coal, gas and pumped storage) for the 2015 constant fuel prices and the carbon cost seen towards the end of 2018 (£37/tCO_2). It also shows the deviation of the average wind over these hours compared to the annual average.

Appendix B

Appendix for Chapter 3

B.1 Cost Pass-through in a Competitive Market: Calculation

Equation (3.3) shows the increase in the system SRMC is a function of the MEF with the CPS applying (μ_1^H), the difference of the SRMCs between coal and gas ($c_C - c_G$), and the change in the coal share at margin ($\Delta\alpha = \alpha_1 - \alpha_0$).

Using the data and results from Chapter 2, during electricity years 2015-2018 the MEFs ($\hat{\mu}_1$) for peak and off-peak are 0.363 and 0.405, respectively.[1] The change in the marginal share of coal ($\widehat{\Delta\alpha}$) during the period is -0.008 and -0.236 for peak and off-peak, respectively.[2] Finally, $(c_C - c_G)$ is estimated to be -€0.323/MWh.[3] Given this, the increase in the system SRMC is €0.366/MWh for peak and €0.481/MWh for off-peak.

The impact of the CPS on the GB electricity price when there is no cross-border trade from Appendix B.4.1 is estimated to be $\widehat{\Delta p^H}$ = €0.635/MWh (s.e.=0.049) for peak periods and $\widehat{\Delta p^H}$ = €0.346/MWh (s.e.=0.060) for off-peak periods.

Based on this, assuming the estimates from Chapter 2 have zero standard errors[4] and are independent with this chapter, the CPS pass-through rate to GB's peak prices is 173%

[1] Chapter 2's period of estimation is 2012-2017 in the Appendix, here we assume the MEF for GB in Q1 2018 is the same as that in Q1 2017. These estimated MEFs use rather low emission factors as they ignore any upstream emissions (from mine/well-head to power station). Using MEFs from other studies may give somewhat different results.

[2] In Chapter 2, we demonstrate that the marginal share of coal/gas is a function of price differences between the SRMC of coal and gas. The price differences is -€0.32/MWh without the CPS, and €11.55/MWh with CPS. Given this, $\alpha_0 = 0.356$ for off-peak and 0.229 for peak; $\alpha_1 = 0.120$ for off-peak and 0.221 for peak.

[3] Precisely, using the notation in Table 3.1, $SRMC^j = VC^j + e^j \cdot EUA$, $j \in \{sccoal, scccgt\}$, where e^j is the emission factor which takes the value of 0.871 for coal and 0.337 for gas, consistent with Chapter 2.

[4] Estimates in Chapter 2 have much smaller standard errors, we assume that parameters whose values are taken from them have zero standard error.

with a 95% confidence interval of 147-200%, and to GB's off-peak prices is 72% with a 95% confidence interval of 47-96%. The weighted average is 133% with a 95% confidence interval of 108-159%.

B.2 Data Appendix

Here we list exactly where the data comes from. GB day-ahead price from Nord Pool at https://www.nordpoolgroup.com/historical-market-data/. French day-ahead price from Epex Spot using Bloomberg. IFA day-ahead capacity from Entso-e at https://transparency.entsoe.eu/. GB load and wind from National Grid ESO at https://demandforecast.nationalgrid.com/efs_demand_forecast/faces/DataExplorer. GB nuclear from Elexon Portal at https://www.elexonportal.co.uk/news/latest. French load, wind and nuclear from RTE at https://www.services-rte.com/en/download-data-published-by-rte.html. NBP gas price, EUA price, and CME coal price are all downloaded from Bloomberg.

B.2.1 M-GARCH Rest of Table 3.2 for IFA

Table B.1 shows the M-GARCH results for other covariates and the ARCH and GARCH terms, as a continuation of Table 3.2.

B.3 Model Extension

Figure B.1 presents Case (b). Similar to Cases (a), the deadweight loss is the trapezium ACDF and $L = 1/2 \cdot (\theta^H + \theta^F) \cdot \Delta m^2 + \Delta m \cdot (p_0^F - p_0^H)$. The social value is the trapezium ABEF and $S = 1/2 \cdot (\theta^H + \theta^F) \cdot m_0^2 + m_0 \cdot (p_0^H - p_0^F)$.

The change in congestion income is also $\Delta R = (p_1^F - p_1^H) \cdot m_1 - (p_0^F - p_0^H) \cdot m_0$, where in this case, $m_1 = -m_0 = K$.

Figure B.2 presents Case (c), without the CPS, H's net supply curve meets F's net supply curve at point A, with prices equalised ($p_0^H = p_0^F$), no congestion income, and imports at m_0. The social value is the triangle AEF, or $S = 1/2 \cdot (\theta^H + \theta^F) \cdot m_0^2$ and the deadweight loss is the triangle ABD, or $L = 1/2 \cdot (\theta^H + \theta^F) \cdot \Delta m^2$. As the interconnector flow is unconstrained with and without the CPS, there is no congestion income before or after and hence no change in congestion revenue. In this case, equations (3.4)-(3.6) still apply, given $p_j^H = p_j^F$.

Figure B.3 presents Case (d), where exactly the same argument as Case (c) can be made. The triangle ABD measures deadweight losses L and the triangle AEF measures social value

Table B.1 M-GARCH Results (Cont'd)

	Unit	(i)	(ii)		(iii)	
Mean Equations						
Great Britain			Off	Peak	Off	Peak
(Constant)		-6.249^{***}	-16.38^{***}	-5.064^{***}	-10.91^{***}	-4.147^{*}
		(1.639)	(1.932)	(1.129)	(2.100)	(1.953)
GB load	GW	0.470^{***}	0.857^{***}	0.404^{***}	0.822^{***}	0.488^{***}
		(0.044)	(0.078)	(0.032)	(0.071)	(0.038)
French load	GW	0.061^{***}	-0.086^{**}	0.108^{***}	-0.053^{*}	0.082^{***}
		(0.019)	(0.026)	(0.015)	(0.024)	(0.019)
GB Nuclear	GW	-0.884^{***}	-0.432^{***}	-0.502^{***}	-0.452^{***}	-0.789^{***}
		(0.085)	(0.117)	(0.074)	(0.108)	(0.116)
French Nuclear	GW	-0.063^{**}	-0.060^{*}	-0.108^{***}	-0.101^{***}	-0.062^{*}
		(0.022)	(0.028)	(0.018)	(0.028)	(0.024)
France						
(Constant)		-29.45^{***}	-23.10^{***}	-33.21^{***}	-22.84^{***}	-32.55^{***}
		(3.047)	(2.699)	(2.853)	(2.748)	(2.980)
GB load	GW	0.156	0.000	0.303^{***}	-0.012	0.304^{***}
		(0.114)	(0.111)	(0.067)	(0.111)	(0.067)
French load	GW	1.022^{***}	0.850^{***}	0.895^{***}	0.854^{***}	0.891^{***}
		(0.036)	(0.036)	(0.034)	(0.036)	(0.034)
GB Nuclear	GW	1.023^{***}	1.227^{***}	1.146^{***}	1.236^{***}	1.096^{***}
		(0.168)	(0.167)	(0.181)	(0.172)	(0.190)
French Nuclear	GW	-0.908^{***}	-0.462^{***}	-0.574^{***}	-0.473^{***}	-0.578^{***}
		(0.046)	(0.045)	(0.047)	(0.046)	(0.048)
Conditional Variance Equations						
Great Britain						
(Constant)		0.400^{***}	2.242^{***}	3.328^{***}	2.227^{***}	1.831^{***}
		(0.080)	(0.265)	(0.239)	(0.265)	(0.284)
ARCH		0.308^{***}	0.609^{***}	1.746^{***}	0.665^{***}	1.132^{***}
		(0.031)	(0.065)	(0.110)	(0.069)	(0.099)
GARCH		0.710^{***}	0.321^{***}	-0.001	0.282^{***}	0.266^{***}
		(0.020)	(0.043)	(0.002)	(0.043)	(0.040)
France						
(Constant)		6.331^{***}	7.019^{***}	5.204^{***}	7.166^{***}	5.428^{***}
		(1.001)	(0.912)	(0.978)	(0.919)	(1.039)
ARCH		0.630^{***}	0.421^{***}	0.303^{***}	0.420^{***}	0.306^{***}
		(0.070)	(0.043)	(0.036)	(0.042)	(0.037)
GARCH		0.244^{***}	0.298^{***}	0.544^{***}	0.291^{***}	0.534^{***}
		(0.061)	(0.060)	(0.055)	(0.060)	(0.057)

Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

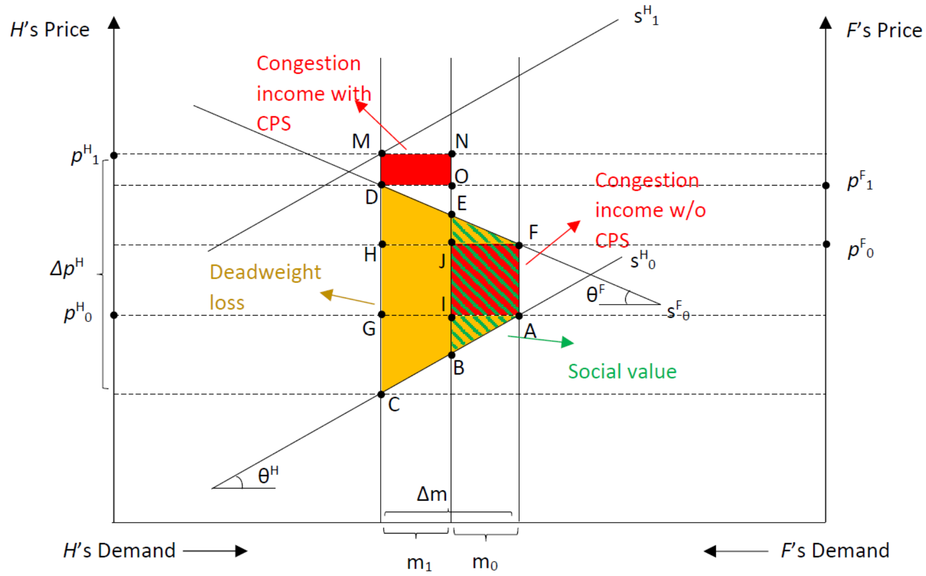


Fig. B.1 Impact of CPS on imports and deadweight losses, Case (b)

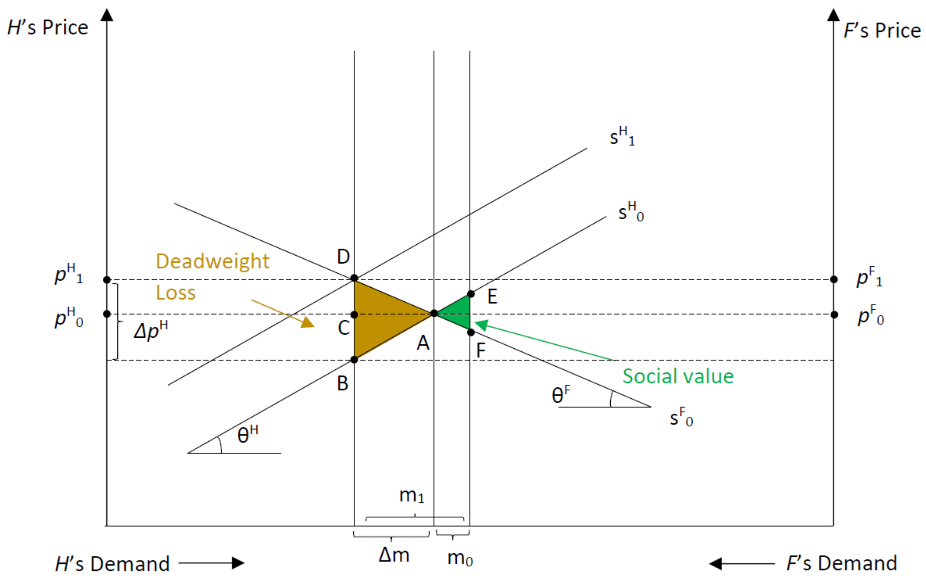


Fig. B.2 Impact of CPS on imports and deadweight losses, Case (c)

S. There is an increase in congestion income $\Delta R = (p_1^H - p_1^F) \cdot m_1$, as shown in Figure B.3 as the rectangle DGHI. Again, equations (3.4)-(3.6) still apply in this case given $p_0^H = p_0^F$.

In Case (e), there is no change in trade or output and hence no distortion, but as H's prices increase, so does the price difference $p_1^H - p_1^F$, with consequential changes in the congestion income $\Delta R = m_0 \cdot (p_1^H - p_0^H)$. As a result, there will be a transfer of revenue from H's consumers to the foreign owners of the interconnectors, who, such as the French system

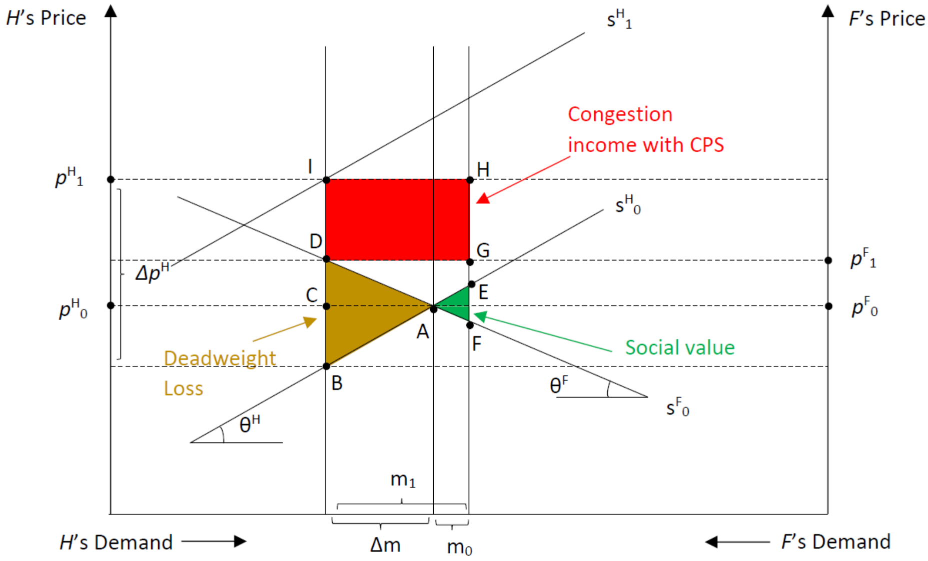


Fig. B.3 Impact of CPS on imports and deadweight losses, Case (d)

operator, shares 50% of the interconnector revenue. Similar to Cases (a) and (b), the social from trading is also $S = 1/2 \cdot (\theta^H + \theta^F) \cdot m_0^2 + m_0 \cdot (p_0^H - p_0^F)$. Finally, given $\Delta m = 0$ and $p_0^F = p_1^F$, equations (3.4)-(3.6) still apply.

B.4 Empirical Results Extension

B.4.1 Estimating counterfactual flows

As before, superscripts H and F represent the Home and Foreign countries, and subscripts 1 and 0 are with and without the CPS. Variables with "$\sim$" above are scenarios with no interconnector trading, and with "$-$" above represents the average over the whole period. Subscripts representing hours are removed to simplify. We implement the following steps to estimate the counterfactual flows:[5]

1. For each hour, given the actual flows[6] ($m_1 > 0$ for importing and < 0 for exporting) and prices (p_1^H and p_1^F), and the marginal effects of wind on prices (θ_1^H, θ_0^H and θ^F, different before and after April 2015 for H),[7] we can calculate the prices when there is

[5] The most ideal way is to include both IFA and BritNed, but it complicates the matters with negligible gain in terms of making the post-econometric results more robust. Therefore, we analyse IFA and BritNed separately.

[6] The day-ahead scheduled IFA flow is collected from RTE.

[7] From Table 3.2, for off-peak periods, $\hat{\theta}_1^H = 0.289$, $\hat{\theta}_0^H = 1.162$ and $\hat{\theta}^F = 1.898$; for peak periods, $\hat{\theta}_1^H = 1.047$, $\hat{\theta}_0^H = 0.826$ and $\hat{\theta}^F = 1.485$.

no trade ($\tilde{p}_1^H$ and $\tilde{p}_1^F$) as

$$\tilde{p}_1^H = \begin{cases} p_1^H + m_1 \cdot \theta_0^H, & \text{before April 2015} \\ p_1^H + m_1 \cdot \theta_1^H, & \text{after April 2015} \end{cases}$$
$$\tilde{p}_1^F = p_1^F - m_1 \theta^F.$$

2. Assuming that without trading, €1/tCO_2 of the British CPS would raise h's price by Δp^H,[8] then the prices *without the CPS* (τ) *and trading*, denoted as $\tilde{p}_0^H$ and $\tilde{p}_0^F$, are

$$\tilde{p}_0^H = \tilde{p}_1^H - \Delta p^H \cdot \tau,$$
$$\tilde{p}_0^F = \tilde{p}_1^F.$$

3. Calculate the interconnector flow where the CPS is not applied (m_0) under the interconnector capacity constraint ($-K < m_0 < K$), taking the Mid Channel loss factor of the interconnector (l) into consideration.[9] Precisely,[10]

$$m_0 = \begin{cases} K, & \tilde{p}_0^H \cdot (1-l) > \tilde{p}_0^F \cdot (1+l) \quad \text{and} \quad K \leq \frac{\tilde{p}_0^H - \frac{1+l}{1-l}\cdot\tilde{p}_0^F}{\frac{1+l}{1-l}\cdot\theta^F + \theta_0^H}, \\ \frac{\tilde{p}_0^H - \frac{1+l}{1-l}\cdot\tilde{p}_0^F}{\frac{1+l}{1-l}\cdot\theta^F + \theta_0^H}, & \tilde{p}_0^H \cdot (1-l) > \tilde{p}_0^F \cdot (1+l) \quad \text{and} \quad K > \frac{\tilde{p}_0^H - \frac{1+l}{1-l}\cdot\tilde{p}_0^F}{\frac{1+l}{1-l}\cdot\theta^F + \theta_0^H}, \\ \frac{\tilde{p}_0^F - \frac{1+l}{1-l}\cdot\tilde{p}_0^H}{\frac{1+l}{1-l}\cdot\theta_0^H + \theta^F}, & \tilde{p}_0^H \cdot (1-l) < \tilde{p}_0^F \cdot (1+l) \quad \text{and} \quad -K < \frac{\tilde{p}_0^F - \frac{1+l}{1-l}\cdot\tilde{p}_0^H}{\frac{1+l}{1-l}\cdot\theta_0^H + \theta^F}, \\ -K, & \tilde{p}_0^H \cdot (1-l) < \tilde{p}_0^F \cdot (1+l) \quad \text{and} \quad -K \geq \frac{\tilde{p}_0^F - \frac{1+l}{1-l}\cdot\tilde{p}_0^H}{\frac{1+l}{1-l}\cdot\theta_0^H + \theta^F}, \\ 0, & \text{otherwise.} \end{cases}$$

[8] Here we assume that the CPS has no direct impact on the French price other than through trading via IFA, which survives statistical tests as discussed in footnote 25 of Chapter 3.

[9] For IFA, the loss factor is $l = 1.17\%$.

[10] Suppose there is no capacity limit and $\tilde{p}_0^H > \tilde{p}_0^F$, then equalising the prices would require

$$(\tilde{p}_0^H - m_0 \cdot \theta_0^H) \cdot (1-l) = (\tilde{p}_0^F + m_0 \cdot \theta_0^F) \cdot (1+l),$$

or

$$m_0 = \frac{\tilde{p}_0^H - \frac{1+l}{1-l} \cdot \tilde{p}_0^F}{\frac{1+l}{1-l} \cdot \theta^F + \theta_0^H}.$$

The derivation is similarly for $\tilde{p}_0^H < \tilde{p}_0^F$.

4. Derive the counterfactual prices under the counterfactual flows:

$$p_0^H = \tilde{p}_0^H - m_0 \cdot \theta_0^H.$$
$$p_0^F = \tilde{p}_0^F + m_0 \cdot \theta^F.$$

5. Given the actual and counterfactual prices for H and F, we can calculate the average actual and counterfactual prices during the period of study (i.e. $\bar{p}_1^H$, $\bar{p}_0^H$ for H, and $\bar{p}_1^H$, $\bar{p}_0^H$ for F). Then, given the average CPS during the period ($\bar{\tau}$), the effect of the CPS on H's price, *counting in the effect of interconnector trading*, is $(\bar{p}_1^H - \bar{p}_0^H)/\bar{\tau}$.

6. From Steps 1-5, the only unknown parameters is Δp^H in Step 2. Table 3.2 gives estimates of the marginal effects of the CPS on H's (GB's) prices ($\widehat{\partial p^H/\partial \tau}$). We iteratively adjust the value of Δp^H in Step 2 and repeat Steps 2-5, until $(\bar{p}_1^H - \bar{p}_0^H)/\bar{\tau}$ in Step 5 is equal to $\widehat{\partial p^H/\partial \tau}$ from Table 3.2 Regression (iii).

7. Once $(\bar{p}_1^H - \bar{p}_0^H)/\bar{\tau}$ and $\widehat{\partial p^H/\partial \tau}$ equate, the associated flows and prices are the counterfactual prices and flows.

Because the undiluted (by trade) effect of the CPS on the GB price (Δp^H in Step 2) is positively correlated with the diluted effect ($(\bar{p}_1^H - \bar{p}_0^H)/\bar{\tau}$ in Step 6, there is a unique Δp^H that equalises $\widehat{\partial p^H/\partial \tau}$ and $(\bar{p}_1^H - \bar{p}_0^H)/\bar{\tau}$ in Step 6.

In these calculations, m_1, p_1^H, p_1^F, τ, K, and l are observed, while θ_1^H, θ_0^H, θ^F and $\partial p^H/\partial \tau$ are estimated separately for peak and off-peak periods.

Using point estimates of θ_1^H, θ_0^H, θ^F and $\partial p^H/\partial \tau$ only gives point estimates of the counterfactuals. To circumvent this problem, we assume that the actual values of θ_1^H, θ_0^H, θ^F and $\partial p^H/\partial \tau$ follow a jointly normal distribution, with mean and variance-covariances equal to the estimated values from Regression (iii). We then apply a Monte Carlo technique to take 500 random draws from the jointly normal distribution, and for each draw, we follow Steps 1-7 to obtain the counterfactual electricity prices and flows and hence the annual average electricity prices, net imports and congestion income. The resulting means and the standard deviations of the counterfactuals are reported in Table 3.3.

B.4.2 Estimating market distortion

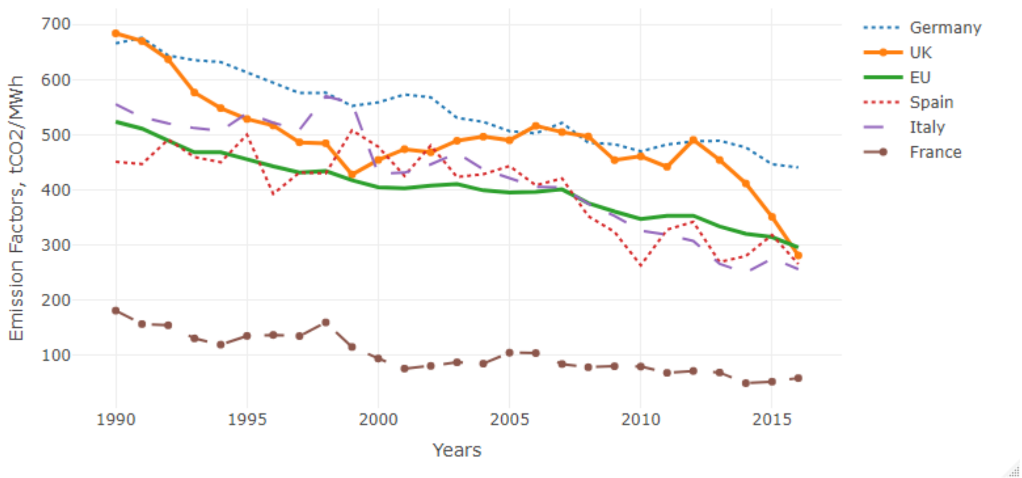
In this subsection, we use the same 500 combinations of counterfactuals to estimate the social value of trading and deadweight losses from asymmetric carbon taxes discussed in Section 3.3.2. In addition, as the CPS does not apply to the increased GB imports, we estimate the loss in the GB government's carbon-tax revenue from the reduction in GB generation displaced,.

From Section 3.6.1 and Appendix B.4.1, given $\hat{\theta}_0^H$ and $\hat{\theta}^F$, and the estimated m_0, Δm, p_0^F and p_0^H, the social value is $1/2 \cdot (\hat{\theta}_0^H + \hat{\theta}^F) \cdot m_0^2 + m_0 \cdot (p_0^H - p_0^F)$, and the deadweight loss is $1/2 \cdot (\hat{\theta}_1^H + \hat{\theta}_1^F) \cdot \Delta m^2 + \Delta m \cdot (p_0^F - p_0^H)$. Finally, the carbon-tax revenue loss is defined as the product between the change in trading volumes (Δm) and GB's marginal emission factors (MEFs), μ_1^H, estimated yearly in Chapter 2.

B.4.3 Estimating the Marginal Emission Factors for France

France is apparently well-connected to Germany, Belgium and The Netherlands and these have higher carbon intensities, as Figure B.4 shows.

Fig. B.4 Carbon intensity of electricity, 1990-2016



Source: European Environment Agency: CO2-emission intensity from electricity generation.

Table B.2 shows the shares of fossil fuels in 2017 in France and its interconnected neighbours. In all these countries gas is the dominant fossil fuel, but coal was more expensive (including the EUA price) than gas in 2017-2018. While gas is more flexible than coal, coal might have been price-setting at least part of the time.

To investigate this further Table B.3 estimates the share of fossil fuel responses to increased fossil demand. For the cases of Belgium, all responses at the margin come from changes in CCGT output. In the case of Germany, Spain, and France, where there are several fossil fuels simultaneously generating, response is measured by looking at the change of each fuel from the previous hour compared to the change in all fossil output over that hour, adjusted to add to 100%. For Germany and Spain, most of the response is from lignite and coal, with a higher MEF, giving the average as 0.68 tCO_2/MWh and 0.48 tCO_2/MWh, respectively. Our estimated German MEF is not very different from the modelled for Germany for 2020 of 0.63 tCO_2/MWh from Böing and Regett [17]. (Northern) Italy has gas and "other" as fossil fuels. While we have no further information on what "other" represents, we assume it is some combinations of lignite, coal, gas and biomass, whose emission factor is half of coal and lignite. The MEF for Italy is taken at 0.38 tCO_2/MWh. Switzerland has no fossil fuels, but it is densely connected to Germany and (Northern) Italy, hence we assume its MEF is the average of those in Germany and Italy, or 0.53 tCO_2/MWh. As Belgium is 100% gas, its MEF is taken at 0.34 tCO_2/MWh. Finally, when the French interconnectors are all congested, the MEF is taken at 0.46 tCO_2/MWh.

Table B.2 Share of different fuels in generation, 2017

Country	Lignite	Coal	Oil	Gas	Other
Germany	22%	11%	0%	5%	
Spain	2%	15%	1%	23%	
Italy				27%	42%
Belgium	0%	0	0%	27%	
France		2%	0%	8%	

Table B.3 Contribution of fossil fuels to flexibility, 2017

	Fossil Fuels					
Country	Lignite	Coal	Oil	Gas	Other	MEF (fossil only)
Germany	29%	45%	1%	25%		0.68
Spain	5%	31%	1%	63%		0.48
Italy				51%	49%	0.53
Switzerland						0.53
Belgium				100%		0.34
France		23%	10%	67%		0.46

Table B.4 Percent time links constrained when IFA unconstrained and MEF for France

	Interconnectors					
	FR-BE	FR-DE	FR-ES	FR-IT	FR-CH	MEF
15-16	67%	83%	53%	56%	64%	0.463
16-17	59%	73%	69%	66%	64%	0.456
17-18	60%	74%	69%	66%	65%	0.461

The next step is to determine the MEF when IFA is uncongested, and that will depend on whether is trading freely with Continental neighbours. If France's borders are all uncongested in any hour then it is assumed that the MEF is the average of the MEFs of the uncongested neighbours plus France, weighted by their shares in their total fossil generation, otherwise it is the weighted average of the remaining uncongested links with France. If France is isolated then it is just the French MEF. The results are shown in table B.4, assuming the same responsive fossil shares in each year.

B.4.4 Estimating the impact of the CPS on BritNed

Due to data availability, our analysis on BritNed runs from January 2015 to September 2018. Electricity load, wind and nuclear generation for The Netherlands and the net transfer capacity of BritNed are collected from the ENTSO-E Transparency Platform. Unfortunately, there is no reliable data source providing BritNed's day-ahead scheduled flow. We simulate the hourly BritNed day-ahead flow using the following algorithm:

- if both the unadjusted price differential (UPD) and adjusted price differential (APD)[11] are greater (or smaller) than zero, the interconnector capacity (K) will be fully used for importing (or exporting);
- if the APD is zero and the UPD is positive, then the day-ahead commercial exchange would be randomly (uniformly) allocated within the interval between zero and K;
- if the APD is zero and the UPD is negative, day-ahead flows would be randomly (uniformly) allocated as a negative number between $-K$ and zero;
- if the APD and UPD have different signs, we assume the direction of flows follows that in the previous hour, and the volume of the flow is randomly taken from the uniform distribution between zero and K.

Due to consistency and data quality concerns, the impact of GB's import/wind and the CPS on the GB prices are taken from Regression (iii) in Table 3.2, and the impact of the Dutch wind on its prices are taken from our new estimates for BritNed. Because of this, we will not include interaction terms between variables and follow Regression (ii)'s specification (but excluding the dummy variable for the French nuclear outages)[12] to study the impact of the Dutch wind on its wholesale prices. The estimation results are reported in Table B.5 as Regression (iv), showing that during off-peak (peak) periods, a 1 GW increase in the Dutch wind generation (or Dutch exports) is associated with a €2.4 (1.8)/MWh reduction in its

[11] Adjusted by the BritNed loss factor of 3%, see BritNed.
[12] The dummy variable is not statistically significant even if we include it in the regressions.

Table B.5 M-GARCH Results, BritNed

		Mean Equations			
		Great Britain		**The Netherlands**	
	Unit	Off	Peak	Off	Peak
(Constant)		-7.226^{**}	-5.675^{*}	-3.926	-16.54^{***}
		(2.302)	(2.332)	(2.631)	(3.181)
GB load	GW	0.501^{***}	0.594^{***}	0.153^{**}	0.464^{***}
		(0.050)	(0.033)	(0.055)	(0.044)
Dutch load	GW	-0.111^{*}	0.114^{*}	0.248^{***}	-0.152^{*}
		(0.052)	(0.055)	(0.052)	(0.074)
GB Nuclear	GW	-0.681^{***}	-0.671^{***}	-0.027	0.239
		(0.144)	(0.152)	(0.134)	(0.194)
Dutch Nuclear	GW	-0.718	-2.907^{***}	-1.703^{***}	-5.061^{***}
		(0.533)	(0.549)	(0.497)	(0.691)
GB wind	GW	-0.432^{***}	-0.916^{***}	-0.051	-0.065
		(0.060)	(0.050)	(0.063)	(0.072)
Dutch wind	GW	-0.060	0.138	-2.377^{***}	-1.814^{***}
		(0.151)	(0.128)	(0.157)	(0.182)
BritNed capacity	GW	-0.862	-3.709^{***}	0.087	0.991
		(0.804)	(0.654)	(0.893)	(0.810)
Coal price	€/MWh$_e$	0.326^{***}	0.349^{***}	0.466^{***}	0.449^{***}
		(0.024)	(0.028)	(0.025)	(0.034)
Gas price	€/MWh$_e$	0.804^{***}	0.823^{***}	0.499^{***}	0.866^{***}
		(0.019)	(0.023)	(0.023)	(0.033)
EUA	€/tCO$_2$	0.469^{***}	0.459^{***}	0.768^{***}	0.551^{***}
		(0.032)	(0.036)	(0.036)	(0.058)
CPS	€/tCO$_2$	0.412^{***}	0.558^{***}	-0.198^{***}	0.021
		(0.035)	(0.034)	(0.042)	(0.046)

	Conditional Variance Equations			
	Great Britain		**The Netherlands**	
	Off	Peak	Off	Peak
(Constant)	2.836^{***}	0.731^{***}	1.816^{***}	1.087^{***}
	(0.407)	(0.139)	(0.394)	(0.245)
ARCH	0.661^{***}	0.348^{***}	0.395^{***}	0.251^{***}
	(0.088)	(0.049)	(0.063)	(0.030)
GARCH	0.278^{***}	0.699^{***}	0.495^{***}	0.742^{***}
	(0.055)	(0.028)	(0.071)	(0.025)

Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

off-peak(peak) wholesale prices. The magnitudes are higher than those in GB and France mainly because the electricity demand in The Netherlands is much lower.

Table B.6 Statistical Measurements for BrtiNed: prices, flows, and congestion revenue

Electricity years	**GB Prices (€/MWh)**			**Dutch Prices (€/MWh)**		
	w. CPS	w/o CPS	Δ	w. CPS	w/o CPS	Δ
15-16	€53.24	€40.52 (0.93)	€12.72 (0.93)	€36.25	€35.24 (0.14)	€1.01 (0.14)
16-17	€51.76	€40.70 (0.81)	€11.07 (0.81)	€35.98	€35.01 (0.14)	€0.97 (0.14)
17-18	€52.70	€42.24 (0.77)	€10.46 (0.77)	€39.87	€38.80 (0.13)	€1.07 (0.13)
Ave.(15-18)	€52.57	€41.15 (0.84)	€11.42 (0.84)	€37.37	€36.35 (0.13)	€1.02 (0.13)
	GB Net Import (TWh)			**Congestion Income (m€)**		
	w. CPS	w/o CPS	Δ	w. CPS	w/o CPS	Δ
15-16	8.21 TWh	3.49 TWh (0.58)	4.72 TWh (0.58)	€134	€60 (3.31)	€74 (3.31)
16-17	7.28 TWh	2.71 TWh (0.56)	4.57 TWh (0.56)	€121	€68 (2.34)	€53 (2.34)
17-18	7.14 TWh	2.11 TWh (0.50)	5.03 TWh (0.50)	€97	€51 (1.94)	€46 (1.94)
Ave.(15-18)	7.54 TWh	2.77 TWh (0.54)	4.77 TWh (0.54)	€117	€59 (2.51)	€58 (2.51)

Standard errors in parentheses.

Note that Table B.5 can be used as a robustness check for our IFA study in Table 3.2. Both studies show some similar magnitudes for the slope coefficients of GB wind, coal and gas prices, as well as EU and British carbon price impacts on GB prices. Perhaps surprisingly, we find the CPS has a negative impact on off-peak Dutch prices. The could be that the data only allow us to have few observations with a CPS of £9.55/tCO_2. Estimates of the effects of the CPS on the wholesale prices are vulnerable to unexpected shocks — for example, the winter of 2016 was one of the warmest in Dutch history, resulting in less domestic heating load and lower electricity prices. Fortunately, this would not affect our post-econometric analysis as we assume that without interconnector trading, the impacts of the CPS on the foreign wholesale prices are zero.

Using the result from Tables 3.2 and B.5, and applying the same steps as Section B.4.1, Table B.6 reports the counterfactuals of the GB and Dutch wholesale prices, as well as the net import and congestion income of BritNed. Our results for BritNed are cosistent with our IFA analysis in Section 3.6.1-3.6.3. During electricity years 2015-2018, the CPS on average raised Dutch wholesale prices by €1.02/MWh, or about 2.8%. About 63% (4.77 TWh) of GB's net import from The Netherlands is due to the CPS, and the associated congestion income almost doubled from €59 m/yr to €117 m/yr.

Table B.7 BritNed: surplus, distortion and losses

Electricity years	**Social Value (m€)**	**Deadweight Loss (m€)**	**GB CPS Rev. Loss (m€)**
15-16	€78	€40.6	€47.2
	(3.69)	(5.17)	(5.76)
16-17	€85	€37.1	€35.4
	(2.70)	(4.41)	(4.44)
17-18	€68	€39.6	€34.8
	(2.15)	(4.60)	(3.51)
Ave. 15-18	€77	€39.1	€39.2
	(2.83)	(4.73)	(4.55)

Standard errors in parentheses.

The effects of the CPS on the Dutch price, GB's net import and congestion revenue from BritNed are more than half of those from our IFA estimates. Although BritNed is half the size of IFA, the slope of the Dutch supply curve (measured by the impact of wind on the Dutch price) is steeper than GB and France because of its smaller electricity load. Table B.7 further shows that during electricity years 2015-2018, the social value of BritNed is €77 m/yr and the deadweight loss is €39.1 m/yr, about half of the social value of IFA's social value and about the same size of the IFA loss. The UK Government has lost about €39.2 million worth of tax revenue, or about 4% of its total CPF receipts in 2017.

Appendix C

Appendix for Chapter 4

C.1 Estimating the Marginal Emission Factor of GB

To estimate the marginal fuel of the GB electricity supply, we replicate Chapter 2 and run the following regressions:

$$\Delta Coal_t = \alpha_0 + \alpha_1 \Delta Wind_t + \alpha_2 \Delta Demand_t + \boldsymbol{\theta}'_{\boldsymbol{Coal}} \boldsymbol{X_t} + \varepsilon_t^{Coal}, \tag{C.1}$$

$$\Delta CCGT_t = \beta_0 + \beta_1 \Delta Wind_t + \beta_2 \Delta Demand_t + \boldsymbol{\theta}'_{\boldsymbol{CCGT}} \boldsymbol{X_t} + \varepsilon_t^{CCGT}, \tag{C.2}$$

$$\Delta PS_t = \gamma_0 + \gamma_1 \Delta Wind_t + \gamma_2 \Delta Demand_t + \boldsymbol{\theta}'_{\boldsymbol{PS}} \boldsymbol{X_t} + \varepsilon_t^{PS}, \tag{C.3}$$

$$\Delta Import_t = \delta_0 + \delta_1 \Delta Wind_t + \delta_2 \Delta Demand_t + \boldsymbol{\theta}'_{\boldsymbol{Import}} \boldsymbol{X_t} + \varepsilon_t^{Import}, \tag{C.4}$$

$$\Delta Hydro_t = \zeta_0 + \zeta_1 \Delta Wind_t + \zeta_2 \Delta Demand_t + \boldsymbol{\theta}'_{\boldsymbol{Hydro}} \boldsymbol{X_t} + \varepsilon_t^{Hydro}, \tag{C.5}$$

where Δ is the first-different operator, and $\boldsymbol{X_t}$ contains dummy variables for each half-hour of the day.

The half-hourly generation-by-fuel-type data comes from Elexon Portal. As the negative values in the columns "import" and "pumped storage" (PS) are missing, we replace the "import" column by the data from the National Grid (NG) Electricity System Operator (ESO), and replace the "pumped storage" by aggregating the PS data from the Elexon P114 data set, which gives half-hourly generation for each Balancing Mechanism Unit.

Table C.1 lists the estimation results of (C.1)-(C.5), and we can calculate the MEF of GB as

$$\widehat{\text{MEF}} = EF_{\text{COAL}} \cdot \hat{\alpha}_2 + EF_{\text{CCGT}} \cdot \hat{\beta}_2 + EF_{\text{PS}} \cdot \hat{\gamma}_2 + EF_{\text{IMPORT}} \cdot \hat{\delta}_2, \tag{C.6}$$

where "$\wedge$" refers to estimates. We assume that $EF_{\text{COAL}} = 0.871$ and $EF_{\text{CCGT}} = 0.337$, consistent with Chapter 2. The values of EF_{PS} and EF_{IMPORT} depend on our assumption on which

Table C.1 Estimating Marginal Fuels

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	89.369^{***}	164.669^{***}	-324.716^{***}	64.180^{***}	6.421^{***}
	(5.109)	(8.574)	(5.322)	(7.507)	(1.304)
$\Delta Wind_t$	-0.125^{***}	-0.676^{***}	-0.123^{***}	-0.053^{***}	-0.017^{***}
	(0.005)	(0.008)	(0.005)	(0.007)	(0.001)
$\Delta Demand_t$	0.190^{***}	0.602^{***}	0.119^{***}	0.059^{***}	0.021^{***}
	(0.001)	(0.003)	(0.002)	(0.002)	(0.000)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.444	0.805	0.467	0.102	0.308
Num. obs.	64469	64469	64469	64469	64469

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

fuel types supply imports and pumped storages. Then, from Table C.1, if we assume all imports and pumped storages come from CCGTs, the MEF is 0.429 tCO_2/MWh; if we assume all imports and pumped storages come from coal plants, the MEF is 0.525 tCO_2/MWh.

Tables C.2 and C.3 report the similar results expect in these cases, we separate the data into peak and off-peak periods, and into weekdays and weekends. From Tables C.2, if we assume all imports and pumped storages come from CCGTs, the MEFs for peak and off-peak periods are 0.434 tCO_2/MWh and 0.410 tCO_2/MWh, respectively. If we assume all imports and pumped storages come from coal plants, the MEFs for peak and off-peak periods are 0.521 tCO_2/MWh and 0.532 tCO_2/MWh. The difference between peak and off-peak is, in fact, statistically significant.

Similarly, from Tables C.3, if we assume all imports and pumped storages come from CCGTs, the MEFs for weekdays and weekends are 0.432 tCO_2/MWh and 0.424 tCO_2/MWh, respectively. If we assume all imports and pumped storages come from coal plants, the MEFs for weekdays and weekends are 0.537 tCO_2/MWh and 0.529 tCO_2/MWh, respectively. The difference is between weekdays and weekends is, again, statistically significant.

C.2 Validity Test Statistics

We use the Augmented Dickey-Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to determine the existence of a unit root in the dependent variables. The ADF test uses Auto-Regression (AR) regressions to determine whether a time series variable is non-stationary, while KPSS is a reversed version which uses stationarity as the null hypothesis.

Table C.2 Estimating Marginal Fuels, Peak *v.s* Off-peak

PEAK PERIODS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	-222.677^{***}	184.696^{***}	190.981^{***}	-175.384^{***}	10.767^{***}
	(7.526)	(11.910)	(6.914)	(10.345)	(2.147)
$\Delta Wind_t$	-0.141^{***}	-0.670^{***}	-0.124^{***}	-0.042^{***}	-0.022^{***}
	(0.006)	(0.009)	(0.005)	(0.008)	(0.002)
$\Delta Demand_t$	0.204^{***}	0.599^{***}	0.094^{***}	0.068^{***}	0.026^{***}
	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.468	0.809	0.246	0.116	0.319
Num. obs.	43263	43263	43263	43263	43263

OFF-PEAK PERIODS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	48.208^{***}	172.591^{***}	-246.820^{***}	34.742^{***}	-8.260^{***}
	(5.154)	(9.936)	(6.736)	(8.816)	(0.722)
$\Delta Wind_t$	-0.090^{***}	-0.689^{***}	-0.118^{***}	-0.081^{***}	-0.006^{***}
	(0.007)	(0.014)	(0.010)	(0.013)	(0.001)
$\Delta Demand_t$	0.146^{***}	0.611^{***}	0.200^{***}	0.029^{***}	0.005^{***}
	(0.003)	(0.005)	(0.004)	(0.005)	(0.000)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.378	0.794	0.619	0.078	0.243
Num. obs.	21206	21206	21206	21206	21206

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table C.3 Estimating Marginal Fuels, Weekdays *v.s* Weekends

WEEKDAYS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	115.033^{***}	162.257^{***}	-377.204^{***}	90.157^{***}	7.026^{***}
	(6.269)	(10.305)	(6.065)	(9.278)	(1.572)
$\Delta Wind_t$	-0.126^{***}	-0.683^{***}	-0.116^{***}	-0.056^{***}	-0.015^{***}
	(0.005)	(0.009)	(0.005)	(0.008)	(0.001)
$\Delta Demand_t$	0.209^{***}	0.564^{***}	0.116^{***}	0.080^{***}	0.022^{***}
	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.471	0.820	0.512	0.125	0.311
Num. obs.	45658	45658	45658	45658	45658

WEEKENDS

	Dependent Variables				
	$\Delta Coal_t$	$\Delta CCGT_t$	ΔPS_t	$\Delta Import_t$	$\Delta Hydro_t$
(Intercept)	62.984^{***}	67.212^{***}	-185.153^{***}	50.585^{***}	12.262^{***}
	(8.743)	(14.967)	(10.205)	(12.439)	(2.370)
$\Delta Wind_t$	-0.118^{***}	-0.666^{***}	-0.138^{***}	-0.047^{***}	-0.022^{***}
	(0.008)	(0.013)	(0.009)	(0.011)	(0.002)
$\Delta Demand_t$	0.182^{***}	0.590^{***}	0.137^{***}	0.060^{***}	0.027^{***}
	(0.003)	(0.005)	(0.003)	(0.004)	(0.001)
Time Dummies	YES	YES	YES	YES	YES
R^2	0.383	0.780	0.463	0.101	0.324
Num. obs.	18811	18811	18811	18811	18811

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The ADF test has very low power (against $I(0)$ alternatives that are close to being $I(1)$), while KPSS has a high possibility of Type I errors (i.e. it tends to over-reject the null hypothesis). Based on this, the two tests give different results, the time series is more likely to be an $I(0)$ process.

Table C.4 Unit Root Tests

	ADF tests*				KPSS tests		
Variables	Lags	Stat.	p-value	Results**	Stat.	p-value	Results**
levels							
GB DA Prices	20	−3.24	0.08	I(1)	0.36	<0.01	I(1)
Coal Prices	0	−1.82	0.69	I(1)	0.31	<0.01	I(1)
Gas Prices	0	−2.46	0.35	I(1)	0.62	<0.01	I(1)
EUA Prices	14	0.22	1.00	I(1)	1.02	<0.01	I(1)
GBP/EUR XR	4	−1.99	0.60	I(1)	0.86	<0.01	I(1)
GB DA Renew. Gen	17	−5.67	0.00	I(0)	0.19	<0.05	I(1)
GB DA Demand	23	−2.66	0.25	I(1)	0.10	>0.10	I(0)
GB Nuclear Gen.	1	−7.73	0.00	I(0)	0.41	<0.01	I(1)
first differences							
ΔGB DA Prices	19	−13.02	0.00	I(0)	0.00	>0.10	I(0)
ΔCoal Prices	0	−37.37	0.00	I(0)	0.10	>0.10	I(0)
ΔGas Prices	7	−15.37	0.00	I(0)	0.06	>0.10	I(0)
ΔEUA Prices	23	−8.00	0.00	I(0)	0.07	>0.10	I(0)
ΔGBP/EUR XR	3	−20.32	0.00	I(0)	0.04	>0.10	I(0)
ΔGB DA Renew. Gen	17	−14.75	0.00	I(0)	0.08	>0.10	I(0)
ΔGB DA Demand	22	−8.08	0.00	I(0)	0.04	>0.10	I(0)
ΔGB Nuclear Gen.	11	−14.37	0.00	I(0)	0.01	>0.10	I(0)

* test with constant and trend terms

** suggested results at 5% significant level

The unit root test results are shown in Table C.4. All ADF tests contain a constant term and a trend term, therefore they test whether the dependent variables are trend stationary. The lag lengths for the test specifications are selected by the Akaike Information Criterion (AIC), where the upper bound for the optimal lag length is determined by the Schwert [135] criterion. Our ADF test results fail to reject the null that all dependent variables in $\boldsymbol{y}_t$ in (4.8) are $I(1)$ processes, whereas the KPSS tests suggest that these variables are not $I(0)$. Therefore, we can safely conclude that all variables in $\boldsymbol{y}_t$ are non-stationary.

The ADF and KPSS tests give contrasting results about the order of integration for the GB day-ahead renewable generation and electricity demand, and the GB nuclear generation. Because of the aforementioned reason — the ADF test suffers from low power, while the

KPSS is vulnerable in front of Type I errors — the three variables are treated as stationary processes.

Table C.5 AIC for Lag Lengths

Criterion	Lag Lengths						
	1	2	3	4	5	6	7
AIC	-13.02	-13.17	-13.15	-13.22*	-13.20	-13.19	-13.17

* optimal lag length suggested by AIC.

The lag lengths for dependent variables, p in (4.8), are determined by the AIC. As Table C.5 shows, the optimal lag length is $p = 4$.

The validity for the VECM requires the dependent variables to be cointegrated. The Johansen and Juselius [85] cointegration tests work on the canonical correlation of $\Delta \boldsymbol{y}_t$ and $\boldsymbol{y}_{t-1}$. The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of m (the number of sequences in $\Delta \boldsymbol{y}_t$) cointegrating vectors. The maximum eigenvalue test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r+1$ cointegrating vectors. The results in Table C.6 indicate one cointegrating equation in the proposed VECM (4.8), and both tests are conducted at the 5% significant level.

C.3 Johansen tests results for Regressions (iii) and (iv)

Tables C.7 and C.8 report the Johansen cointegration tests for the VECM specifications discussed in Sections 4.5.2 and 4.5.2, respectively. Both tables suggest two cointegration equations.

Table C.6 Cointegration Tests

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0.14812	269.14	79.34	0.00
At most 1	0.01644	49.99	55.25	0.13
At most 2	0.01182	27.34	35.01	0.26
At most 3	0.00798	11.08	18.40	0.38
At most 4	0.00009	0.13	3.84	0.72

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.14812	219.14	37.16	0.00
At most 1	0.01644	22.66	30.82	0.35
At most 2	0.01182	16.25	24.25	0.39
At most 3	0.00798	10.96	17.15	0.32
At most 4	0.00009	0.13	3.84	0.72

* denotes rejection of the hypothesis at the 0.05 level.

** MacKinnon-Haug-Michelis (Mackinnon et al. [95]) p-values.

Table C.7 Cointegration Tests for Regression (iii), Peak *v.s.* Off-peak

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0.20132	515.91	107.35	0.00
At most 1*	0.10959	208.61	79.34	0.00
At most 2	0.01636	49.93	55.25	0.14
At most 3	0.01187	27.39	35.01	0.26
At most 4	0.00795	11.06	18.40	0.38
At most 5	0.00011	0.15	3.84	0.70

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.20132	307.30	43.42	0.00
At most 1*	0.10959	158.68	37.16	0.00
At most 2	0.01636	22.54	30.82	0.36
At most 3	0.01187	16.33	24.25	0.39
At most 4	0.00795	10.92	17.15	0.32
At most 5	0.00011	0.15	3.84	0.70

* denotes rejection of the hypothesis at the 0.05 level.

** MacKinnon-Haug-Michelis (Mackinnon et al. [95]) p-values.

Table C.8 Cointegration Tests for Regression (iv), Weekdays *v.s.* Weekends

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None*	0.51475	293.41	107.35	0.00
At most 1*	0.42186	153.13	79.34	0.00
At most 2	0.09995	46.83	55.25	0.22
At most 3	0.08100	26.40	35.01	0.31
At most 4	0.04737	10.02	18.40	0.48
At most 5	0.00309	0.60	3.84	0.44

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None*	0.51475	140.28	43.42	0.00
At most 1*	0.42186	106.30	37.16	0.00
At most 2	0.09995	20.43	30.82	0.52
At most 3	0.08100	16.39	24.25	0.38
At most 4	0.04737	9.41	17.15	0.45
At most 5	0.00309	0.60	3.84	0.44

* denotes rejection of the hypothesis at the 0.05 level.

** MacKinnon-Haug-Michelis (Mackinnon et al. [95]) p-values.

Appendix D

Appendix for Chapter 5

D.1 Solution Method

Model (5.16) is a non-linear programming (NLP) problem, more specifically it is a quadratically constrained quadratic programming (QCQP) problem. Since both the objective function and the inequality constraints are convex and twice continuously differentiable, the barrier method (Boyd et al. [21]) is used for solving the problem.

The goal is to approximately formulate the inequality constrained problem as an equality constrained problem so that Newton's method can be applied. First, the model can be rearranged as:

$$
\begin{aligned}
\min \quad & -\mathbb{E}[\phi(\mathbf{x})] \\
\\
\text{subject to} \quad & \mathbb{E}[d_t] = E_t^s, \quad \forall t \\
& \mathbb{E}[d_t] = \mathbb{E}[d_{0,t}] \left(1 + \varepsilon_{t,t} \frac{\pi_t - \pi_{0,t} + r_t}{\pi_{0,t}} + \sum_{t'=1}^{T} \varepsilon_{t,t'} \frac{\pi_{t'} - \pi_{0,t'} + r'_t}{\pi_{0,t}} \right) \cdot \kappa_t, \quad \forall t \\
& D^{\text{Min}} - \sum_{t=1}^{T} \mathbb{E}[d_t] \leq 0, \\
& \sum_{t=1}^{T} \mathbb{E}[d_t] - D^{\text{Max}} \leq 0, \\
& \pi_t^{\text{Min}} - \pi_t \leq 0, \quad \forall t \\
& \pi_t - \pi_t^{\text{Max}} \leq 0, \quad \forall t \\
& \sum_{t=1}^{T} \mathbb{E}[d_t] \pi_t - \delta \cdot \sum_{t=1}^{T} \mathbb{E}[d_{0,t}] \pi_{0,t} \leq 0.
\end{aligned}
$$

Then we can make the inequality constraints implicit in the objective function:

$$\begin{aligned}\min \quad & -\mathbb{E}[\phi(\mathbf{x})] + I_{-}(D^{\mathrm{Min}} - \sum_{t=1}^{T}\mathbb{E}[d_t]) + I_{-}(\sum_{t=1}^{T}\mathbb{E}[d_t] - D^{\mathrm{Max}}) \\ & + \sum_{t=1}^{T} I_{-}(\pi_t^{\mathrm{Min}} - \pi_t) + \sum_{t=1}^{T} I_{-}(\pi_t - \pi_t^{\mathrm{Max}}) \\ & + I_{-}(\sum_{t=1}^{T}\mathbb{E}[d_t]\pi_t - \delta \cdot \sum_{t=1}^{T}\mathbb{E}[d_{0,t}]\pi_{0,t})\end{aligned} \tag{D.1}$$

$$\begin{aligned}\text{subject to} \quad & \mathbb{E}[d_t] = E_t^s, \quad \forall t \\ & \mathbb{E}[d_t] = \mathbb{E}[d_{0,t}]\left(1 + \varepsilon_{t,t}\frac{\pi_t - \pi_{0,t} + r_t}{\pi_{0,t}} + \sum_{t'=1}^{T}\varepsilon_{t,t'}\frac{\pi_{t'} - \pi_{0,t'} + r_t'}{\pi_{0,t}}\right) \cdot \kappa_t, \quad \forall t\end{aligned}$$

where $I_{-}(\cdot) : \mathbf{R} \rightarrow \mathbf{R}$ is the indicator function for the non-positive reals,

$$I_{-}(u) = \begin{cases} 0 & u \leq 0 \\ \infty & u > 0. \end{cases}$$

Then, when $u \leq 0$, i.e. the inequality constraint holds, $I_{-}(u)$ equals 0, adding no penalty to (D.1). However, when $u > 0$, i.e. the inequality constraint fails to hold, $I_{-}(u)$ equals infinity, boosting (D.1) to infinity as well. Hence while minimize (D.1), the inequality constraint would always hold.

Note that since here the indicator function is not differentiable, we approximate the indicator function $I_{-}(\cdot)$ by $\hat{I}_{-}(\cdot)$:

$$\hat{I}_{-}(u) = -(1/\lambda)\log(-u).$$

The accuracy of the approximation depends on the value of λ, a positive index number. As λ increases, the approximation becomes more accurate. Similar to $I_{-}(\cdot)$, $\hat{I}_{-}(\cdot)$ is convex, non-decreasing, and takes the value ∞ when u is greater than 0. However, unlike $I_{-}(\cdot)$, $\hat{I}_{-}(\cdot)$ is differentiable and closed: it increases to ∞ as u increases from negative to 0.

Then, we substitute $I_{-}(\cdot)$ by $\hat{I}_{-}(\cdot)$ and obtain

$$\begin{aligned} \min \quad & -\mathbb{E}[\phi(\mathbf{x})] + \frac{1}{\lambda} g(\mathbf{x}) \\ \text{subject to} \quad & \mathbb{E}[d_t] = E_t^s, \quad \forall t \\ & \mathbb{E}[d_t] = \mathbb{E}[d_{0,t}] \left(1 + \varepsilon_{t,t} \frac{\pi_t - \pi_{0,t} + r_t}{\pi_{0,t}} + \sum_{t'=1}^{T} \varepsilon_{t,t'} \frac{\pi_{t'} - \pi_{0,t'} + r_t'}{\pi_{0,t}} \right) \cdot \kappa_t, \quad \forall t, \end{aligned}$$

where $g(\mathbf{x})$ is the logarithm barrier, and

$$\begin{aligned} g(\mathbf{x}) = & -\log(-D^{\text{Min}} + \sum_{t=1}^{T} \mathbb{E}[d_t]) - \log(-\sum_{t=1}^{T} \mathbb{E}[d_t] + D^{\text{Max}}) - \sum_{t=1}^{T} \log(-\pi_t^{Min} + \pi_t) \\ & - \sum_{t=1}^{T} \log(-\pi_t + \pi_t^{\text{Max}}) - \log(-\sum_{t=1}^{T} \log[d_t]\pi_t + \delta \cdot \sum_{t=1}^{T} \mathbb{E}[d_{0,t}]\pi_{0,t}). \end{aligned}$$

Then Newton's method can be implemented to solve this. If we slightly simplify the notation and multiply the objective function by λ, it becomes

$$\min \quad -\lambda\, \mathbb{E}[\phi(\mathbf{x})] + g(\mathbf{x})$$

The quality of approximation improves as λ grows. When λ is large, however, the objective function $-\lambda\phi(\mathbf{x}) + g(\mathbf{x})$ is hard to minimise by Newton's method because its Hessian varies rapidly near the boundary. As a result, the barrier method solves a sequence of the problem by increasing λ at each step, and starts the Newton minimization at the solution of the problem for the previous value of λ. Formally, the barrier method can be summarised as Table D.1 (Boyd et al. [21]).

From Algorithm 1, the barrier method is a double iterative algorithm — we have the outer iteration when we gradually increase λ by a factor μ, and compute $\mathbf{x}^{\star}(\lambda)$ from the previously computed $\mathbf{x}^{\star}(\lambda)$; and the inner iteration when we apply the Newton process to compute $\mathbf{x}^{\star}(\lambda)$.

In section 3.6, we use AIMMS, a high-level modelling software to solve the NLP problem.

Table D.1 Algorithm: barrier method

Given

starting with a value $\lambda := \lambda^{(0)} > 0$, solve the barrier problem (D.1) using Newton's method to get $\mathbf{x}^{(0)} := \mathbf{x}^{\star}(\lambda)$.

Do

for barrier parameter $\mu > 1$, update $\lambda^{(1)} = \mu\lambda^{(0)}$ for $i = 1, 2, ...,$ do:

1. solve the barrier problem at $\lambda := \lambda^{(i)}$ using Newton's method initialised at $\pi_t^{(i-1)}$ to produce $\mathbf{x}^{(i)} := \mathbf{x}^{\star}(\lambda^{(i)})$;
2. stop if $\frac{m}{\lambda} \leq \varepsilon$, where m is the number of inequalities and ε is a desired level of accuracy;
3. Else, update $\lambda^{(i+1)} = \mu\lambda^{(i)}$.